

**A NEURAL NETWORK SOLUTION
TO PREDICTING WIND SPEED
AT CAPE CANAVERAL'S
ATLAS LAUNCH PAD**

THESIS

Kenneth P. Cloys, Captain, USAF

AFIT/GM/ENP/00M-03

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

20001113 013

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the U. S. Government.

AFIT/GM/ENP/00M-03

A NEURAL NETWORK SOLUTION TO PREDICTING WIND SPEED
AT CAPE CANAVERAL'S ATLAS LAUNCH PAD

THESIS

Presented to the Faculty

Department of Engineering Physics

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Meteorology

Kenneth P. Cloys, B.S.

Captain, USAF

March 2000

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

A NEURAL NETWORK SOLUTION TO PREDICTING WIND SPEED
AT CAPE CANAVERAL'S ATLAS LAUNCH PAD

Kenneth P. Cloys, B.S.
Captain, USAF

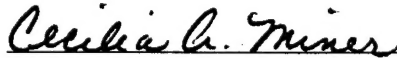
Approved:



Michael K. Walters (Chairman)

2 MAR 2000

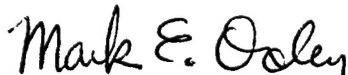
date



Cecilia A. Miner (Member)

2 Mar 2000

date



Mark E. Oxley (Member)

2 Mar 2000

date

Acknowledgements

I would like to thank my thesis advisor, Lt Col Walters, for the independence he granted me in this study. He always had just the right balance of guidance and trust to permit me to investigate the world of neural networks and their applicability to solving the problem of forecasting winds.

Lt Col Miner's suggestions were particularly helpful in bringing out important aspects of this research that I would have otherwise omitted. She also reminded me several times that negative or uninteresting results are not necessarily bad results.

Dr Oxley was especially patient with me as I tried to explain my approach to him and clarify obscure points about the direction I was taking in my work.

Although not officially part of my advisory committee, Lt Col Stephen Alsing provided tremendous support while I was learning the basics of MATLAB and its neural network toolbox. When I recall some of the questions I asked him, I am amazed he ever understood what I was trying to say. I am grateful for his help.

My sponsor from the 45th Weather Squadron, Patrick Air Force Base, Mr William Roeder, proved to be an invaluable resource throughout the planning and development of this study. I asked him numerous questions, and he always responded professionally, courteously, and soundly.

The results of this study may not change the world, and the folks at 45 WS may never use a neural net to predict their winds, but this thesis represents the culmination of a tremendous amount of work. My wife, Joyce, deserves special recognition for putting up with me and without me while I gave this project all I had. She took on much of the

stress of running our household that should have been mine. This research would have remained incomplete without her help, support, and understanding.

Kenneth P. Cloys

Table of Contents

	Page
Acknowledgements	iii
List of Figures	vii
List of Tables.....	xi
Abstract	xiii
1. Introduction	1-1
Background.....	1-1
Problem Statement.....	1-3
Thesis Outline.....	1-3
2. Literature Review	2-1
3. Neural Network Theory	3-1
Biological Basis	3-1
Network Architecture	3-2
Connection Weights.....	3-4
Network Training.....	3-6
4. Methodology	4-1
Database Description	4-1
Network Inputs	4-5
Targets	4-11
Network Development.....	4-11
Network Training.....	4-14
Network Testing	4-16
Variation on the Original Method.....	4-18
Reliability Intervals	4-19
5. Results and Discussion.....	5-1
Original Method.....	5-1
Variation on the Method.....	5-2
Reliability Intervals	5-17
Operational Use	5-19

	Page
Further Study	5-20
Conclusion	5-26
Appendix A. Time Series of Peak Wind Speed	A-1
Appendix B. Period of Record Data Gaps	B-1
Appendix C. MATLAB Program Codes	C-1
Appendix D. Performance Tables	D-1
Appendix E. 8-hour Forecasts with Reliability Intervals	E-1
Bibliography	BIB-1
Vita	Vita-1

List of Figures

Figure	Page
1.1. 30-minute Maximum Peak Wind Speeds at 90 feet above the Atlas Launch Pad.....	1-2
3.1. Schematic of a Biological Neuron	3-1
3.2. Typical Architecture of a Feed-Forward Neural Network with a Tapped-Delay Line	3-3
4.1. Geography of the CCAS/KSC Area	4-3
4.2. Scatter Plot of Peak Wind Speed vs. Time of Day (UTC) for the 25 Data Periods Used	4-6
4.3. Scatter Plot of Peak Wind Speed vs. Direction for the 25 Data Periods Used ...	4-8
4.4. Scatter Plot of Peak Wind Speed vs. Directional Deviation for the 25 Data Periods Used	4-9
4.5. Phase Diagrams for 30-minute Maximum Peak Wind Speed	4-10
4.6. Typical Progression of Mean Squared Error (MSE) during Network Training.....	4-15
4.7. Climatological Values of 30-minute Maximum Peak Winds for All Wintertime Observations	4-17
4.8. Histogram of 30-minute Maximum Peak Wind Speeds for the 25 Data Periods Used	4-18
5.1. Mean Absolute Error (MAE) vs. Forecast Valid Time for Data Subset 3.....	5-17
5.2. Half-hour Forecasts from 24 January – 1 February 1996 Using the Variation Method	5-18
5.3. As in Fig. 5.2, but for 1-hour Forecasts during 5-13 December 1995.....	5-19
5.4. As in Fig. 5.2, but for 1.5-hour Forecasts during 14-22 December 1996.....	5-20
5.5. As in Fig. 5.2, but for 2-hour Forecasts during 23 February – 7 March 1996..	5-21

5.6.	As in Fig. 5.2, but for 2.5-hour Forecasts during 6-21 January 1997	5-22
5.7.	As in Fig. 5.2, but for 3-hour Forecasts during 24 November – 8 December 1996.....	5-23
5.8.	As in Fig. 5.2, but for 3.5-hour Forecasts during 25 November – 2 December 1997.....	5-24
5.9.	As in Fig. 5.2, but for 4-hour Forecasts during 29 January – 6 February 1997.....	5-25
5.10.	As in Fig. 5.2, but for 4.5-hour Forecasts during 4-18 March 1998.....	5-26
5.11.	As in Fig. 5.2, but for 5-hour Forecasts during 1-10 March 1997.....	5-27
5.12.	As in Fig. 5.2, but for 5.5-hour Forecasts during 8-17 November 1998	5-28
5.13.	As in Fig. 5.2, but for 6-hour Forecasts during 2-13 December 1997.....	5-29
5.14.	As in Fig. 5.2, but for 6.5-hour Forecasts during 14-20 January 1999	5-30
5.15.	As in Fig. 5.2, but for 7-hour Forecasts during 5-11 January 1998.....	5-31
5.16.	As in Fig. 5.2, but for 7.5-hour Forecasts during 21-31 March 1999	5-32
5.17.	As in Fig. 5.2, but for 8-hour Forecasts during 25 January – 4 February 1999.....	5-33
5.18.	Forecasts and Reliability Intervals for 24 January – 1 February 1996	5-34
5.19.	As in Fig. 5.18, but for 4-18 March 1998	5-35
5.20.	As in Fig. 5.18, but for 8-17 November 1998.....	5-35
A.1.	5-minute Peak Wind Speed, 2-12 March 1995.....	A-1
A.2.	5-minute Peak Wind Speed, 19-26 March 1995.....	A-2
A.3.	5-minute Peak Wind Speed, 4-13 November 1995	A-2
A.4.	5-minute Peak Wind Speed, 28 November – 5 December 1995	A-3
A.5.	5-minute Peak Wind Speed, 5-13 December 1995.....	A-3
A.6.	5-minute Peak Wind Speed, 24 January – 1 February 1996.....	A-4

A.7.	5-minute Peak Wind Speed, 11-21 February 1996	A-4
A.8.	5-minute Peak Wind Speed, 23 February – 7 March 1996	A-5
A.9.	5-minute Peak Wind Speed, 15-31 March 1996	A-5
A.10.	5-minute Peak Wind Speed, 24 November – 8 December 1996	A-6
A.11.	5-minute Peak Wind Speed, 14-22 December 1996	A-6
A.12.	5-minute Peak Wind Speed, 6-21 January 1997	A-7
A.13.	5-minute Peak Wind Speed, 29 January – 6 February 1997	A-7
A.14.	5-minute Peak Wind Speed, 1-10 March 1997	A-8
A.15.	5-minute Peak Wind Speed, 25 November – 2 December 1997	A-8
A.16.	5-minute Peak Wind Speed, 2-13 December 1997	A-9
A.17.	5-minute Peak Wind Speed, 5-11 January 1998	A-9
A.18.	5-minute Peak Wind Speed, 14-23 January 1998	A-10
A.19.	5-minute Peak Wind Speed, 4-18 March 1998	A-10
A.20.	5-minute Peak Wind Speed, 8-17 November 1998	A-11
A.21.	5-minute Peak Wind Speed, 30 November – 8 December 1998	A-11
A.22.	5-minute Peak Wind Speed, 14-20 January 1999	A-12
A.23.	5-minute Peak Wind Speed, 25 January – 4 February 1999	A-12
A.24.	5-minute Peak Wind Speed, 2-21 March 1999	A-13
A.25.	5-minute Peak Wind Speed, 21-31 March 1999	A-13
E.1.	Forecasts and Reliability Intervals for 5-13 December 1995	E-1
E.2.	Forecasts and Reliability Intervals for 14-22 December 1996	E-2
E.3.	Forecasts and Reliability Intervals for 23 February – 7 March 1996	E-2

E.4.	Forecasts and Reliability Intervals for 6-21 January 1997	E-3
E.5.	Forecasts and Reliability Intervals for 24 November – 8 December 1996.....	E-3
E.6.	Forecasts and Reliability Intervals for 25 November – 2 December 1997.....	E-4
E.7.	Forecasts and Reliability Intervals for 29 January – 6 February 1997	E-4
E.8.	Forecasts and Reliability Intervals for 1-10 March 1997	E-5
E.9.	Forecasts and Reliability Intervals for 2-13 December 1997	E-5
E.10.	Forecasts and Reliability Intervals for 5-11 January 1998	E-6
E.11.	Forecasts and Reliability Intervals for 14-20 January 1999	E-6
E.12.	Forecasts and Reliability Intervals for 21-31 March 1999	E-7
E.13.	Forecasts and Reliability Intervals for 25 January – 4 February 1999	E-7

List of Tables

Table	Page
4.1. Summary Statistics for Data Periods with No Gaps	4-4
4.2. Summary of Development Phase Results	4-13
5.1. Results from 29 January – 6 February 1997 (Original Method)	5-2
5.2. Results from 1-10 March 1997 (Original Method)	5-3
5.3. Results from 2-13 December 1997 (Original Method)	5-4
5.4. Results from 25 January – 4 February 1999 (Original Method)	5-5
5.5. Results from 23 February – 7 March 1996 (Original Method)	5-6
5.6. Results from 24 November - 8 December 1996 (Original Method)	5-7
5.7. Results from 29 January – 6 February 1997 (Variation)	5-8
5.8. Results from 1-10 March 1997 (Variation)	5-9
5.9. Results from 2-13 December 1997 (Variation)	5-10
5.10. Results from 25 January – 4 February 1999 (Variation)	5-11
5.11. Results from 5-13 December 1995 (Variation)	5-12
5.12. Results from 23 February – 7 March 1996 (Variation)	5-13
5.13. Results from 24 November – 8 December 1996 (Variation)	5-14
5.14. Results from 14-23 January 1999 (Variation)	5-15
5.15. Results from 21-31 March 1999 (Variation)	5-16
B.1. Period of Record Data Gaps	B-1
D.1. Results from 5-13 December 1995 (Original Method)	D-1
D.2. Results from 5-11 January 1998 (Original Method)	D-2

D.3.	Results from 24 January – 1 February 1996 (Variation).....	D-3
D.4.	Results from 14-22 December 1996 (Variation).....	D-4
D.5.	Results from 6-21 January 1997 (Variation).....	D-5
D.6.	Results from 25 November – 2 December 1997 (Variation)	D-6
D.7.	Results from 5-11 January 1998 (Variation).....	D-7
D.8.	Results from 4-18 March 1998 (Variation).....	D-8
D.9.	Results from 8-17 November 1998 (Variation)	D-9

Abstract

This thesis demonstrates the potential for using time-delay neural networks to provide Launch Weather Officers (LWOs) at 45th Weather Squadron (45 WS) with advance warning of wintertime (November-March) peak wind speeds at the Atlas launch pad. The 45 WS provides weather support to the United States space program at Cape Canaveral Air Station, NASA's Kennedy Space Center, and Patrick Air Force Base. Due to the complex wintertime environment produced by the effects of friction and instability, 45 WS LWOs consider wintertime launch pad winds their toughest forecast challenge.

Neural networks were developed, trained, and tested using observations of wintertime peak wind speed, wind direction, and directional deviation collected from March 1995 through March 1999 by 45th Space Wing's Weather Information Network Display System. Using current and past values of the observed elements, the networks produced 16 forecasts of peak wind speed. The first forecast was valid for 30 minutes past forecast start time, the second for 1 hour past start time, etc., up to 8 hours past start time, for any start time.

Network performance was compared to three other forecasting options: persistence, climatology, and randomly selecting wind speeds from a climatologically based distribution. For forecasts at the end of the forecast period, networks that were tested with data near in time to the networks' training data showed skill over the other forecasting options.

A new confidence measure for neural network forecasts based on mean absolute error was also developed. Confidence for shorter forecast times was not necessarily higher than for longer forecast times.

The results of this thesis provide a baseline for measuring future attempts at forecast improvements and establish the neural network approach as a potential means of enhancing peak wind speed prediction accuracy, especially for forecasts late in the forecast period.

A NEURAL NETWORK SOLUTION TO PREDICTING WIND SPEED AT CAPE CANAVERAL'S ATLAS LAUNCH PAD

1. Introduction

1.1 Background

Six to eight hours before a rocket launch from the United States Air Force's Atlas launch pad (located in southeast Florida), mission controllers need wind forecasts for their launch and Mobile Service Tower rollback decisions. When the Mobile Service Tower is rolled back, the rocket is left unsupported and exposed to the wind, so Launch Weather Officers (LWOs) must be highly confident that peak wind thresholds will not be exceeded. The disastrous consequences of unexpected high winds are obvious, but false alarms lead to costly and time consuming launch scrubs.

Figure 1.1 shows a time series of 20 consecutive days of 30-minute maximum peak wind speeds at 90 feet above the Atlas launch pad. The 30-minute maximum at a given time step is defined as the highest wind that occurred during the 15 minutes before and after the time step. Several rapid increases are evident in Figure 1.1 (around time steps 300, 1500, and 2000, for example), as are at least two periods of relatively small changes in speed (time steps 900-1200 and 4600-4800).

Time series of wind speed data are highly non-linear and do not represent analytical solutions of equations that describe the wind's behavior. For example, see

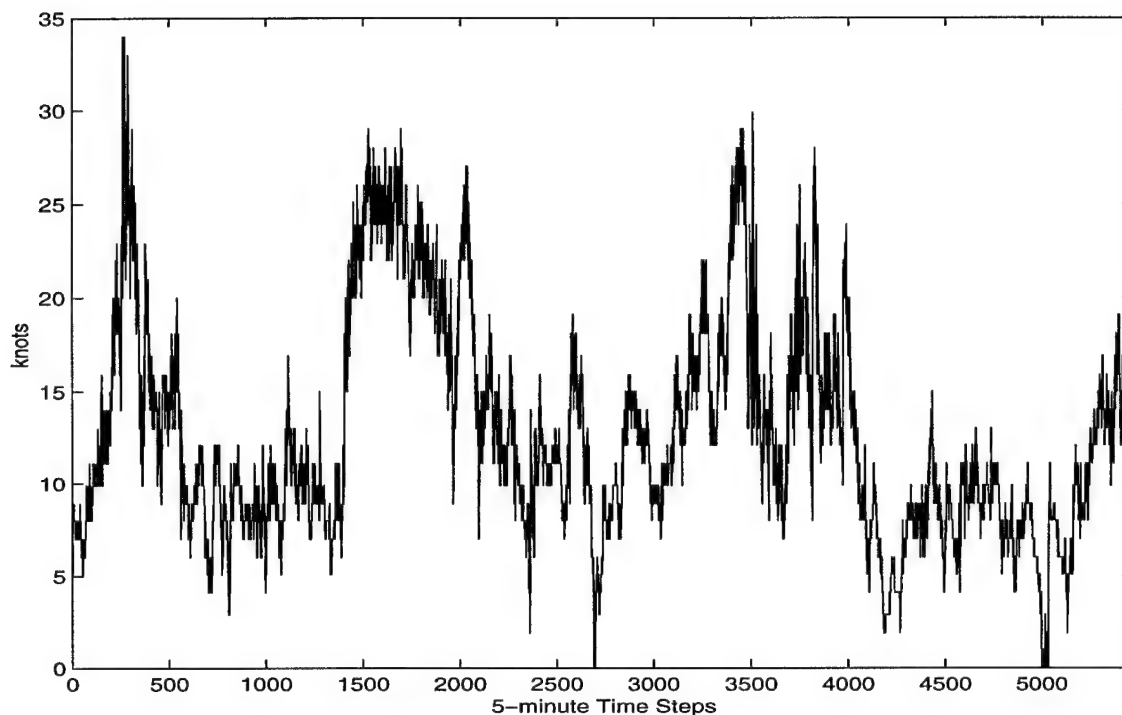


Figure 1.1. 30-minute Maximum Peak Wind Speeds at 90 feet above the Atlas Launch Pad. The non-linear nature of wind speed data is evident, but a low-frequency sinusoidal pattern is also apparent.

Appendix A, which contains time series of the 5-minute peak winds observed during the data periods used in this study. Artificial neural networks, however, have proven capable of predicting future values of similar non-linear series (e.g., stock market indices [Saad et al. (1998)] and electricity demand [Khotanzad et al. (1997)] to a high degree of accuracy using only past series values. Elsner and Tsonis (1992) investigated a time series of sea surface temperatures and concluded that neural networks are capable of short-term predictions even if the underlying dynamics generating the data are chaotic. McCann (1992) put it this way: "A neural network is an artificial-intelligence tool that excels in pattern recognition. This tool can become another means of enhancing a forecaster's pattern-recognition ability."

The current research used a feed-forward back-propagation network with a three-step tapped-delay input. Unlike the recurrent network used by Storch (1999), which fed its intermediate forecasts back as inputs, the network trained and tested in the current study used only observed values of the predictor set as inputs. Using tapped-delay inputs incorporated the memory aspect intuitively necessary for improving on a persistence forecast. Moreover, the tapped-delay network avoided the incestuous nature of recurrent networks, which tend to propagate the effects of poor forecasts through several future generations of forecasts.

1.2 Problem Statement

Accurately predicting the elevated point peak wind speeds at the Cape Canaveral Air Station / Kennedy Space Center (CCAS/KSC) launch pads in winter is the 45 WS LWO's greatest short-term forecast challenge. A more accurate method of forecasting launch pad winds is necessary to ensure the safe, efficient employment of the nation's aerospace assets.

1.3 Thesis Outline

The following chapters detail efforts to address the problem of predicting wintertime launch pad winds using artificial neural networks. Chapter 2 summarizes applicable previous work in the area of neural nets. Chapter 3 presents a short introduction to artificial neural network theory. The specific neural network methodology used in this research can be found in Chapter 4. Chapter 5 summarizes the results and conclusions of this study and offers suggestions for further work on this problem.

2. Literature Review

The literature is replete with the history, theory, and applications of artificial neural networks (also known simply as "neural networks" and "neural nets") covering a broad range of disciplines. Target recognition (Dean, 1994), voice recognition (Lindsey, 1991), and pilot head movement prediction (Lindsey, 1991) are just a few of the areas where neural nets enjoy success.

In the last several years, meteorologists have also recognized neural networks' inherent abilities to "learn" the rules associated with the non-linear mechanisms driving diverse atmospheric processes. Neural networks have been used successfully in predicting thunderstorms (McCann, 1992), tornadoes (Marzban and Stumpf, 1996), and precipitation amounts (Kuligowski and Barros, 1998 and Hall et al., 1999).

Since this research focuses on predicting a time series, this literature review concentrates on similar forecasting work. Dewdney (1997) questions the validity of the neural net method and expresses concern for the apparent mystery surrounding neural networks. Other sources, however, present artificial neural networks as outstanding candidates for predicting nonlinear time series, suggesting similar success is possible in forecasting wind speed.

In 1992, McCann stated, "... neural nets ... have the potential to solve pattern-recognition problems that other methods have not yet been able to solve," and "... the patterns associated with a particular weather phenomenon are not always easy to see."

As Figure 1.1 suggests, wind speed data are good candidates for neural networks' pattern-recognition abilities. Any diurnal, synoptic, and seasonal signals that may be

present in the overall pattern often obscure each other, and the data take on an apparently random, patternless distribution.

Time series of financial indices also frequently appear to have no pattern. Heim (1995), however, not only showed that a neural network can skillfully predict the motion of a financial index, but also developed a confidence table for assessing the validity of the network's predictions. While forecasting financial time series with a neural network that adapted its time delays as well as its connection weights, Gainey (1993) showed that even a highly chaotic system is predictable.

Much of the criticism in the literature centers on the "black box" mystique surrounding neural networks. Not knowing exactly how neural nets arrive at solutions is troubling to some. Dewdney (1997), referring to the synaptic table of connection weights from a trained network, says, "The knowledge embedded in that table [is] inaccessible to science and therefore valueless as a scientific resource. Science is about accessible knowledge, not numerical hodge-podges." This, however, is a matter of form over function: Although a forecaster may not explicitly understand *how* a network obtains its predictions, the quality of the network's outputs is what matters.

Good network forecasts are the only justification most meteorologists would need for using neural nets operationally, but the weight table of a trained network may contain scientific value and accessible knowledge after all.

... neural networks ... are phenomenological in that they assess the qualitative characteristics of the underlying system's dynamics and make short-term predictions based on that knowledge without providing a physical understanding of the mechanisms that might be operating within the system. However, successful predictions with such models can lead to useful hypotheses concerning, for example, why certain inputs are associated with stronger connection weights

compared to others--which can readily be interpreted as a hypothesis concerning the physical nature of the system. (Elsner and Tsonis, 1992)

Roadknight et al. (1997) even go so far as to extract rules from their neural network's weight tables to develop models of environmental processes. The authors synthesize prognostic equations using the network's connection weights that have the highest relative importance.

Dewdney (1997) continues his concerns, noting,

For the rest of us, neural nets have had a something-for-nothing quality, one that imparts a peculiar aura of laziness and a distinct lack of curiosity about just how good these computing systems are. No human hand (or mind) intervenes; solutions are found as if by magic; and no one it seems, has learned anything.

Responding to these concerns, Roeder (1999) points out, "Interestingly enough, if one developed a set of highly stratified statistical regressions as a climatological application, these objections wouldn't be raised. But in essence, that is what a neural net does, a continuously stratified non-linear regression." Furthermore, humans obviously program the network and determine the functions the algorithm uses to adjust the connection weights. Moreover, if a neural network accurately predicts launch pad winds, the payoff is immediate and tangible, even if no one learns anything about the wind.

McCann (1992) may have addressed this matter best: "... it is practically impossible to understand the 'black box.' The conclusions of this analysis are not very satisfying to scientists. Acceptance comes from how well the networks have learned real patterns."

3. Neural Network Theory

3.1 Biological Basis

Artificial neural networks are loosely patterned after the brain's neuronal connections. Neurons, the fundamental building blocks of the nervous system, are connected along dendritic and axonal paths at junctures known as synapses (see Figure 3.1).

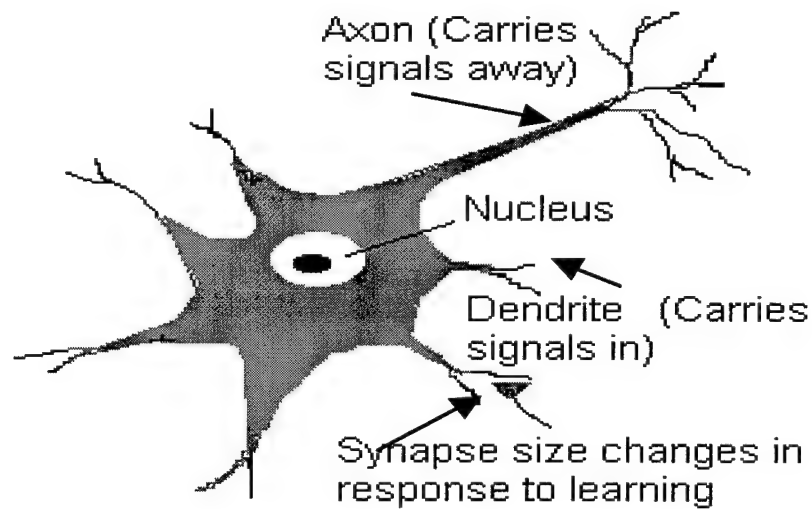


Figure 3.1. Schematic of a Biological Neuron. Axons carry signals from the neuron to other neurons; dendrites carry signals into the neuron from other neurons. Axon-dendrite junctions occur at synapses. (After NewWave Intelligent Business Systems, 1999.)

A neuron receives inputs as chemical stimuli along its dendrites. Some inputs to the neuron are inhibitory and lower its electrical potential; some are excitatory and raise its potential. The neuron sums its inputs, and if the total exceeds the neuron's activation

threshold, the neuron fires and sends its own signal along its axon to other neurons. The brain's nervous system is highly interconnected, and the firing of billions of neurons and relaying of signals among neurons allow us to remember, learn, and create.

Although a diagram of an artificial neural network's architecture shows neurons (also called "nodes") connected to other neurons, the resemblance to the human brain ends here. Neural nets, including the ones used in this research, are nothing more than mathematical algorithms designed to minimize certain error functions and thereby optimize the solution to a given problem. In fact, for small networks, the values in the weight/bias table determined during training can be used to calculate forecasts by hand. Rogers, et al. (1990) put it this way: "... beware of anybody who implies that his/her artificial neural network performs some function the way the brain does."

Statements like, "The beauty of a neural network is that it is continually learning as it processes," and "It fixes its processes based on the data or knowledge it acquires," (Heim, 1995) mislead the uninitiated. Terms like "learning," "adapting," and "training" are normally used in the biological sense, but they have made their way irreversibly into the neural net jargon and are frequently applied to certain features of network processes. Although these terms are inaccurately anthropomorphic, they do provide a convenient way to describe many aspects of neural network behavior and will be used here.

3.2 Network Architecture

The architecture of a neural network defines how many inputs, "hidden" layers, and outputs the network has, as well as how many nodes each layer contains and how the layers and nodes interact with each other. Figure 3.2 shows a typical architecture for the

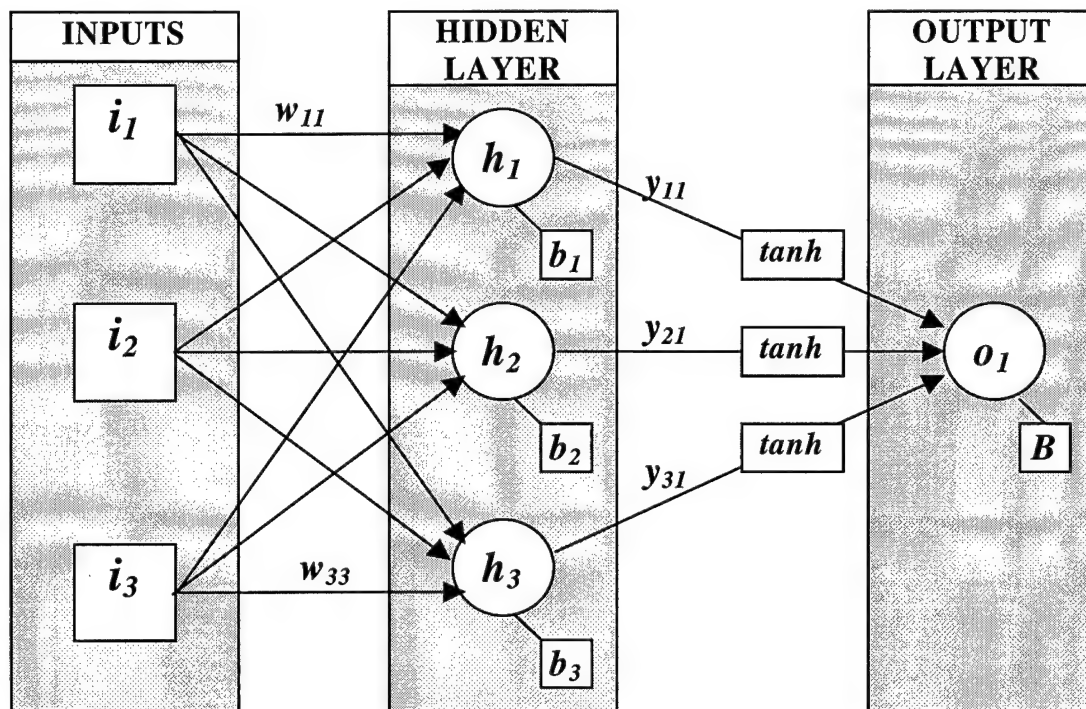


Figure 3.2. Typical Architecture of a Feed-Forward Neural Network with a Tapped-Delay Line. Top input (i_1) corresponds to the current value of the input (predictor) series; i_2 and i_3 refer to previous values of the series after one and two delays, respectively. Lines with arrows indicate connection weights. For clarity, only two hidden layer weights, w_{11} and w_{33} , are shown. All three output layer weights, y_{11} , y_{21} , and y_{31} , are shown.

type of network used in this thesis. (The specific architecture for this research is discussed in detail in Chapter 4.)

In the figure, all inputs are connected to the network's hidden layer, which is shown with three nodes (h_1 , h_2 , and h_3). The hidden layer nodes sum the weighted contributions from each input, add a bias term (b_k), and apply a sigmoidal transfer function (\tanh) to the result. These intermediate results are then weighted and summed by the output layer neuron (o_1). This final node, o_1 , applies a linear transfer function to the weighted sum and adds a bias term (B) to produce the network forecast.

The number of output nodes generally matches the number of values to be predicted. For example, this study requires 16 outputs, one for each half-hour forecast in the 8-hour forecast period.

The term "hidden" for the middle layer of neurons is unfortunate, and this nomenclature perpetuates the aura of voodoo surrounding the neural network method. Calling the layer "hidden," however, simply means it has no interaction with the world outside the network. Any number of hidden layers is possible, but a two-layer network (a network with one hidden and one output layer) using enough hidden layer nodes can approximate any functional relationship between the input and output variables (Park et al., 1996). The current research uses a two-layer architecture with 10 neurons in the hidden layer. (The input set is not considered a layer.)

3.3 Connection Weights

Inputs are linked to hidden layer nodes via connection weights. Weights are initially set to random values between -1 and 1. As the first set of inputs is presented to the network, each input value i_j is multiplied by the corresponding weight w_{jk} connecting i_j to hidden layer node h_k . All input-weight products $i_j w_{jk}$ entering a hidden layer node are summed, and a bias term b_k is added. The result is the value of the hidden layer node. For example, the value of hidden layer node h_1 in Figure 3.2 is calculated as follows:

$$h_1 = i_1 w_{11} + i_2 w_{21} + i_3 w_{31} + b_1 \quad (1)$$

where each i_j is an input value, each w_{jk} is the connection weight from the input to the hidden layer, and b_1 is the bias term.

Just as there are weights connecting inputs to hidden layer nodes, there are weights connecting hidden layer nodes to network output nodes. The results of applying a non-linear transfer function to the hidden layer values become inputs in determining output values. Although several options for the transfer function exist, MATLAB's default for feed-forward tapped-delay neural nets, the hyperbolic tangent, was used in this research. The choice is not critical as long as the function is monotonically increasing and is bounded with upper and lower limits (Kuligowski and Barros, 1998). The requirement for a monotonic increase is to ensure a one-to-one mapping between hidden layer results and network outputs.

The values of each hidden layer node after applying the transfer function are multiplied by each hidden node's corresponding weight connecting the node to the output layer. These products are then summed and another bias term is added. In Figure 3.2, the value of the output neuron is calculated as follows:

$$o_1 = \tanh(h_1)y_{11} + \tanh(h_2)y_{21} + \tanh(h_3)y_{31} + B \quad (2)$$

where each h_k is computed as in (1), each w_{kl} is the connection weight from a hidden layer node to the output node, and B is the output node's bias term.

To summarize, the network output in Figure 3.2 is computed as follows:

$$o_1 = \sum_{k=1}^3 \left[\tanh \left(\sum_{j=1}^3 i_j w_{jk} + b_k \right) \right] y_{k1} + B \quad (3)$$

3.4 Network Training

The network's weights and biases, the keys to the network's ability to predict accurately, are determined during network training. Weights and biases are initially set to random values but are changed as the network is shown successive input-target pairs. The network compares its forecast to the given target value and computes a measure of the forecast error, typically the mean squared error between the forecast and the target. With each iteration or “epoch” of this process, the weights and biases are adjusted so as to minimize the error function. In a sense, the error is “back-propagated” through the network, hence the name “feed-forward *back-propagation* neural network.” (The “feed-forward” part refers to the fact that prediction information only flows in one direction, from input to output.)

Just as interactions among biological neurons allow us to learn and generalize, the interconnectivity among nodes of an artificial neural network is central to the network's ability to learn relationships and discern patterns among exemplar input-output pairs. Training results in a network that has “learned” the relationships between the inputs and targets. Given similar but new inputs, the network uses the weights and biases to predict new outputs.

4. Methodology

4.1 Database Description

The 45th Space Wing's Weather Information Network Display System (WINDS) includes 44 towers that record meteorological data every 1-5 minutes. This study only used peak wind speed, direction, and directional deviation data from the Atlas WINDS Tower (Space Launch Complex 36) at 90 feet above the ground. The recorded wind speeds, directions, and directional deviations are 5-minute averages of measurements taken every second. The peak wind speed is the highest of the 300 wind speeds measured during the previous 5 minutes.

The neural networks used in this research predict the maximum peak winds that will occur within 16 thirty-minute periods centered at each forecast valid time. Valid times occur every half hour after forecast start time until 8 hours after forecast start time. For example, if forecast start time is 1200, the first forecast valid time is 1230. The neural net's first forecast is for the maximum peak wind that will occur between 1215 and 1245. The second forecast is for the maximum peak wind between 1245 and 1315. The 16th forecast is for the maximum peak wind between 1945 and 2015.

Maximum peak wind was chosen as the predictand because even one occurrence of peak wind speed over Cape Canaveral Air Station / Kennedy Space Center's (CCAS/KSC's) User Launch Commit Criteria puts the launch sequence in Condition Red. An average of expected peak winds, although possibly more representative of future conditions as a whole, might mask a predicted wind speed above the criteria threshold.

Since launch criteria differ among vehicles and even among configurations for the same vehicle, the neural networks were trained to predict actual peak wind speeds, not simply the likelihood of wind speed exceeding a certain threshold.

Four years of wintertime (November-March) data from the WINDS tower at the Atlas launch pad were used to train feed-forward back-propagation neural networks. Roeder (1999) says a problem exists in the peak wind database collected before 1994. Therefore, this work uses data from March 1995 through March 1999. Since different atmospheric mechanisms cause hot and cold season winds, and hot season winds at CCAS/KSC are typically easier to forecast, only cold season winds were examined.

Roeder explains that CCAS/KSC's summer winds are usually light and driven by subtle patterns. Such light and slowly changing winds are relatively easy to forecast. In winter, however, complex interactions among land- and sea-breezes, frictional and stability environments, and synoptic systems make predicting launch pad peak winds difficult. Figure 4.1 shows the complicated arrangement of land-water boundaries around CCAS/KSC.

The database period of record encompassed 651 days, of which 179 (27.5%) contained gaps where one or more data fields were not recorded. (See Appendix B for a complete listing of data gaps.) Gaps ranged from 5 minutes (one time step) to 3½ days (over 900 time steps).

Since the neural network method requires continuous data series for mapping inputs to target outcomes, the 25 longest no-gap periods from the original database were used in developing, training, and testing the neural net used in this thesis. The longest no-gap period covered almost exactly 19 days (5,474 5-minute time steps); the shortest

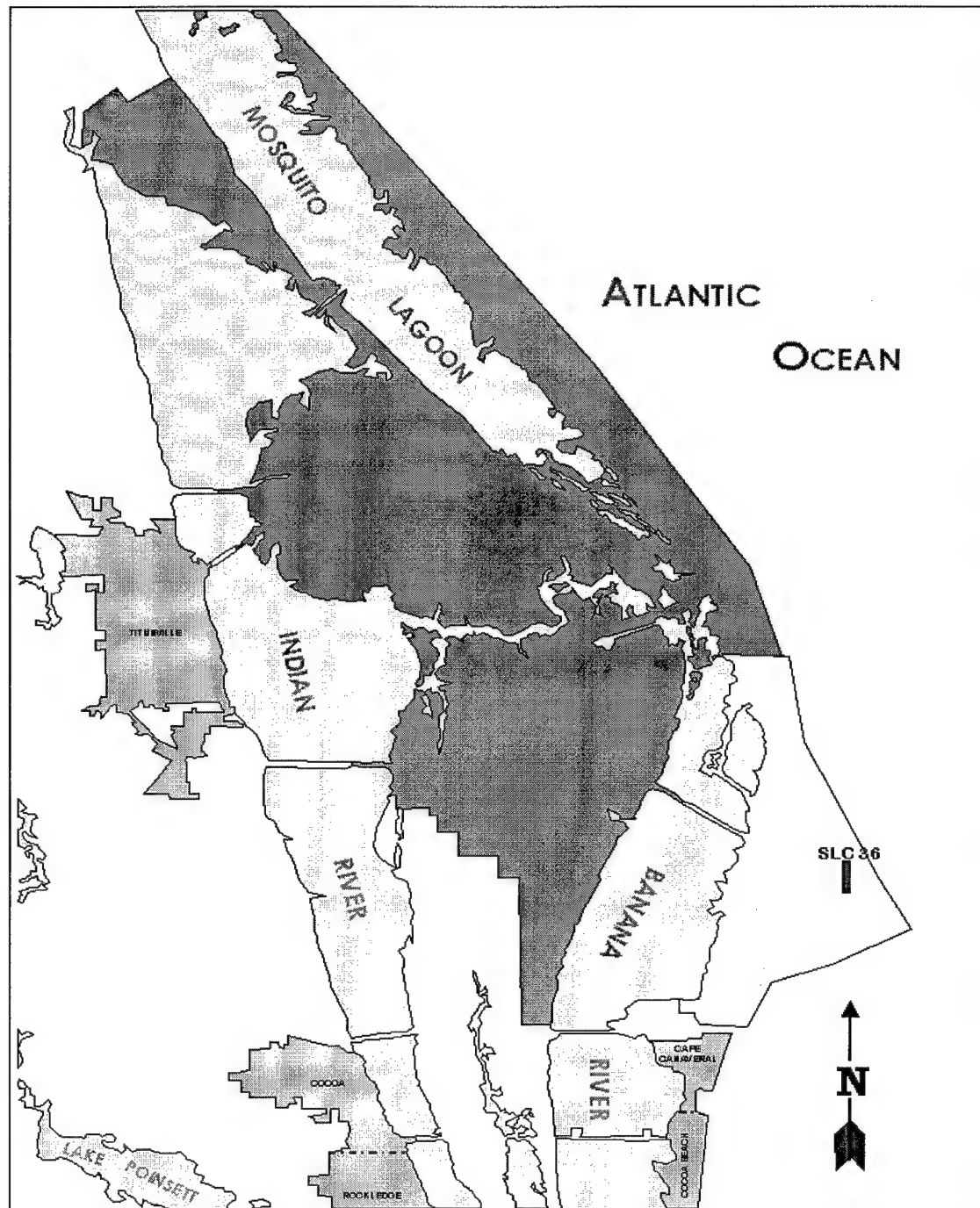


Figure 4.1. Geography of the CCAS/KSC Area. Note the intricate system of land-water boundaries. Land-, river-, and sea-breezes, although somewhat predictable if considered separately, combine to complicate the wind forecasting process. Land-water arrangements as complex as those depicted here make wind forecasting particularly difficult. Data for this study were taken from Space Launch Complex (SLC) 36, located at the lower right in the figure.

covered a little over 6 days (1,931 time steps). Although it would have been possible to synthesize missing observations using techniques like linear interpolation and cubic splines, this approach was rejected in favor of relying solely on “pure” data. Table 4.1 summarizes the continuous data sets used in this research.

Table 4.1. Summary Statistics for Data Periods with No Gaps

Subset	Start Date	End Date	Time Steps	Mean Peak Speed (kts)	Std Dev of Peak Speeds (kts)	Max Peak Speed (kts)
1	2 Mar 95	12 Mar 95	2647	14.76	6.65	42.00
1	19 Mar 95	26 Mar 95	2232	13.55	4.62	29.90
1	5 Nov 95	13 Nov 95	2297	14.39	5.46	34.00
1	28 Nov 95	5 Dec 95	1931	9.86	4.23	22.00
1	11 Feb 96	21 Feb 96	2887	12.95	5.59	35.00
1	15 Mar 96	31 Mar 96	4896	13.75	5.93	49.00
1	14 Jan 98	23 Jan 98	2782	13.09	5.17	32.10
1	30 Nov 98	8 Dec 98	2421	9.47	2.98	25.10
1	2 Mar 99	21 Mar 99	5474	12.83	5.90	34.00
2	24 Jan 96	1 Feb 96	2422	12.90	6.68	32.10
2	14 Dec 96	22 Dec 96	2289	14.51	5.30	29.00
2	6 Jan 97	21 Jan 97	4390	13.04	5.78	29.00
2	25 Nov 97	2 Dec 97	2178	12.00	4.82	25.10
2	4 Mar 98	18 Mar 98	4048	15.26	5.52	37.90
2	8 Nov 98	17 Nov 98	2513	9.69	4.20	25.10
2	14 Jan 99	20 Jan 99	1992	10.15	4.19	21.00
2	21 Mar 99	31 Mar 99	2801	11.27	4.78	28.00
3	5 Dec 95	13 Dec 95	2134	12.85	7.18	33.00
3	23 Feb 96	7 Mar 96	4032	12.27	5.59	29.00
3	24 Nov 96	8 Dec 96	3325	15.15	5.13	29.90
3	29 Jan 97	6 Feb 97	2353	8.81	3.61	21.00
3	1 Mar 97	10 Mar 97	2621	12.57	4.49	27.00
3	2 Dec 97	13 Dec 97	3003	10.70	4.44	32.10
3	5 Jan 98	11 Jan 98	1953	12.95	5.08	32.10
3	25 Jan 99	4 Feb 99	2930	11.88	7.29	42.00
Overall			<u>72551</u>	12.61	5.68	49.00
Subset 1			27567	12.90	5.66	49.00
Subset 2			22633	12.62	5.61	37.90
Subset 3			22351	12.22	5.75	42.00

Each of the 25 data periods described above was randomly assigned to one of three subsets. The first subset (containing nine periods) was used to develop and test a preliminary neural network to determine the best architecture to use in the next phase, network training. The training phase used the second subset (eight periods) to determine weights and biases for a new network. Finally, the trained network was tested on data from the third subset (eight periods).

After a description of the input and target data used in this study, the development, training, and testing of the network are described in detail below.

4.2 Network Inputs

The following elements were used to compute inputs to the neural networks: peak wind speed, time of day (UTC), wind direction, directional deviation, and 30-minute maximum peak wind. In winter, local time at CCAS/KSC is UTC minus 5 hours.

One-hour moving averages of observed peak wind speed were chosen in an effort to minimize the turbulent noise in the peak wind input signal (Roeder, 1999). To capture the trend in the signal, previous one-hour averages were also included. Previous values of an input element are known as “delays,” thus the network designator “*time-delay* neural network.” The development phase (discussed in the next section) estimated the best number of delays to use.

MATLAB’s neural network software requires all inputs to use the same number of delays. Thus, current and delayed one-hour moving averages of all elements were used as network inputs.

Figure 4.2 shows a scatter plot of peak wind speed vs. time of day. The effects of the nocturnal temperature inversion are evident around 1200 UTC (0700 L). The inversion is well established by this time of day, creating a physical barrier that keeps stronger winds above the inversion. The 1200 UTC minimum in the scatter plot confirms this analysis.

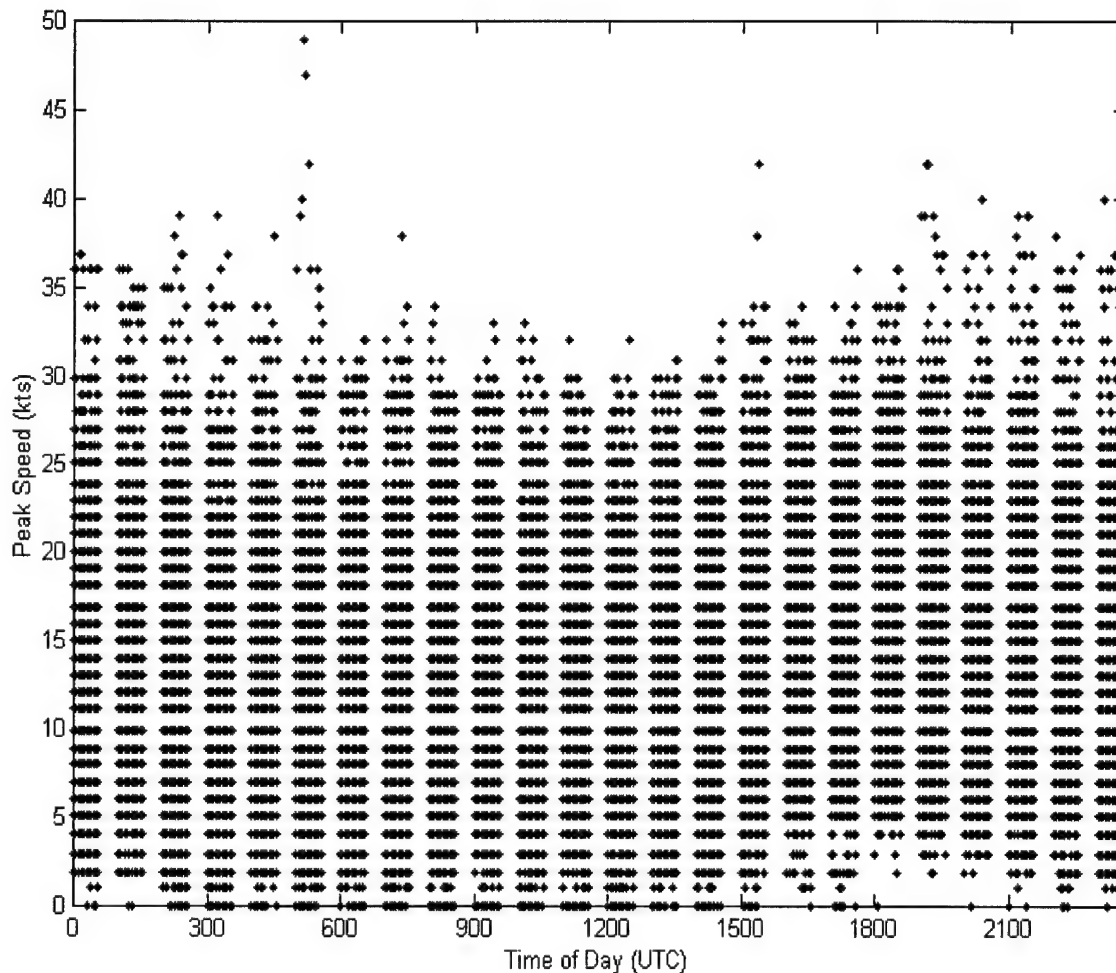


Figure 4.2. Scatter Plot of Peak Wind Speed vs. Time of Day (UTC) for the 25 Data Periods Used. Lower peak speeds tend to occur during the morning. Time of day was included as a network input in an attempt to capture the diurnal effects on peak wind speed.

Values of time of day were normalized to $[-1, 1]$ as follows:

$$\text{TIME} = \sin(2\pi T / 2355) \quad (4)$$

where T is the four-digit military time from the original database. Normalization removed the time input singularity in going from 2355 to 0000 and avoided having high-magnitude values of time dominate the network input signal.

Similar difficulties with input values of wind direction were corrected by normalizing the original values of direction θ to $[-1, 1]$ using

$$\text{DIR} = \sin(2\pi\theta / 360) \quad (5)$$

Wind direction was included as an input because higher peak winds seemed to have preferred directions. Figure 4.3 shows a cluster of higher winds from the east-southeast (around 100 degrees).

Figure 4.4 indicates the clear tendency for higher peak wind speeds to occur in conjunction with smaller directional deviations. Thus another network input was directional deviation, defined as the standard deviation over all the 1-second wind directions observed during the previous 30 minutes.

Phase diagrams for various delays of 30-minute maximum peak wind speeds are displayed in Figure 4.5. At the shorter delays (5 minutes and 1 hour), the plots are fairly concentrated along the diagonal line. This suggests high correlations at short delays, so persistence forecasts were expected to show at least moderate skill for short forecast lengths. To take advantage of the high autocorrelation suggested by these plots, moving averages of 30-minute maximum peak winds (the forecasted element itself) were included as inputs to the neural network.

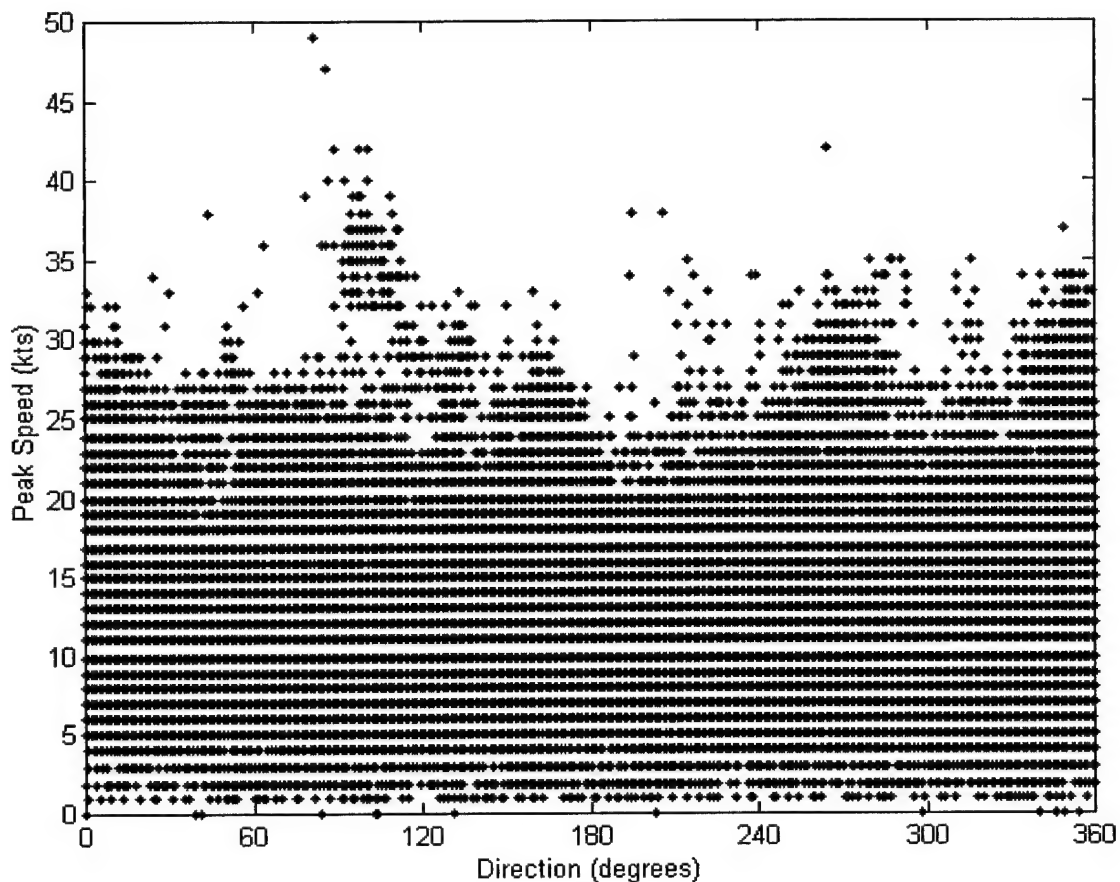


Figure 4.3. Scatter Plot of Peak Wind Speed vs. Direction for the 25 Data Periods Used. Most peak winds above 35 knots are from the east-southeast, but other clusters of high winds are evident from the west and north. Including wind direction as an input gives the network an opportunity to take advantage of directional influences on peak wind speed.

At the 8-hour delay, the points are more widely dispersed around the diagonal, however, implying higher errors from using persistence late in the forecast period. Many of the plots of 24-hour delays are so far from the diagonal that using peak wind speed from the same time the previous day as a predictor would not be expected to contribute to forecast skill.

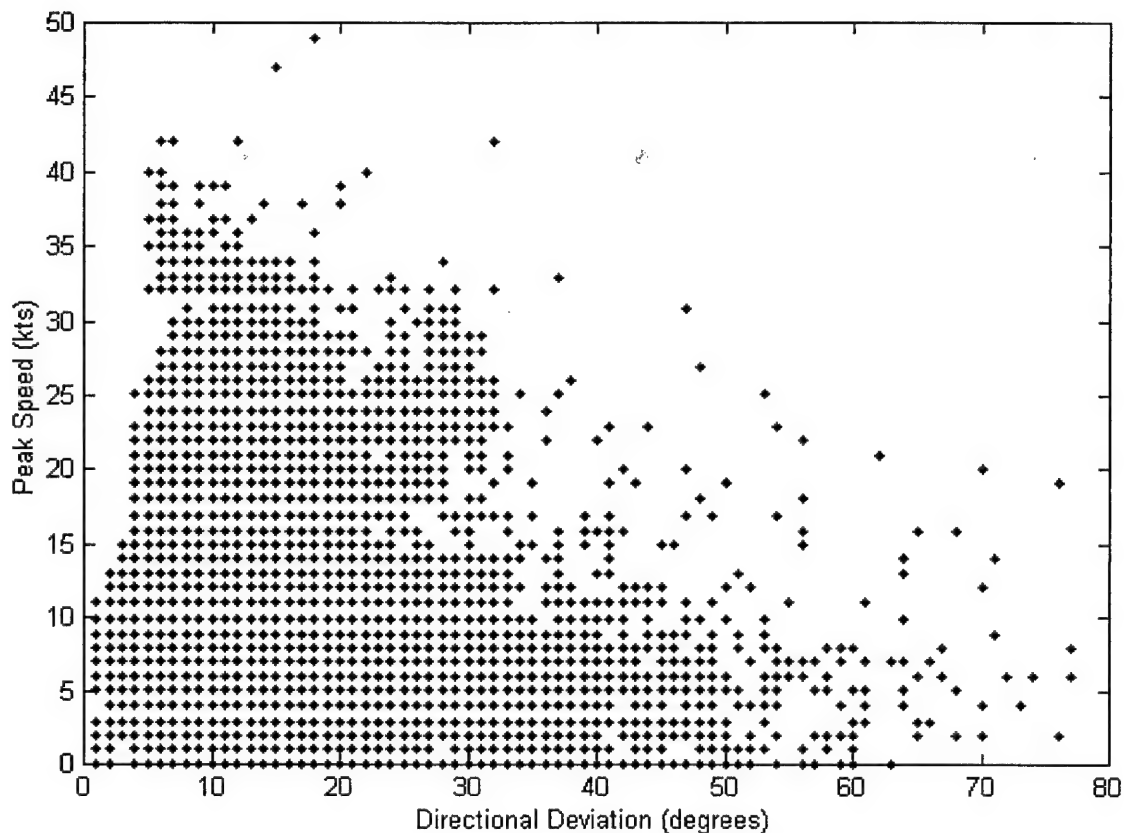


Figure 4.4. Scatter Plot of Peak Wind Speed vs. Directional Deviation for the 25 Data Periods Used. Higher peak speeds tend to occur in conjunction with lower directional deviations, so directional deviation was chosen as a network input.

The final input to the neural network incorporated a measure of the acceleration of the change in wind speed. A vector of the differences between successive values of peak wind speed was calculated. Successive differences of values in this new vector were then calculated to determine network inputs. The acceleration of wind speed differences was considered a viable predictor, because peak wind speed series generally do not gradually approach their maxima.

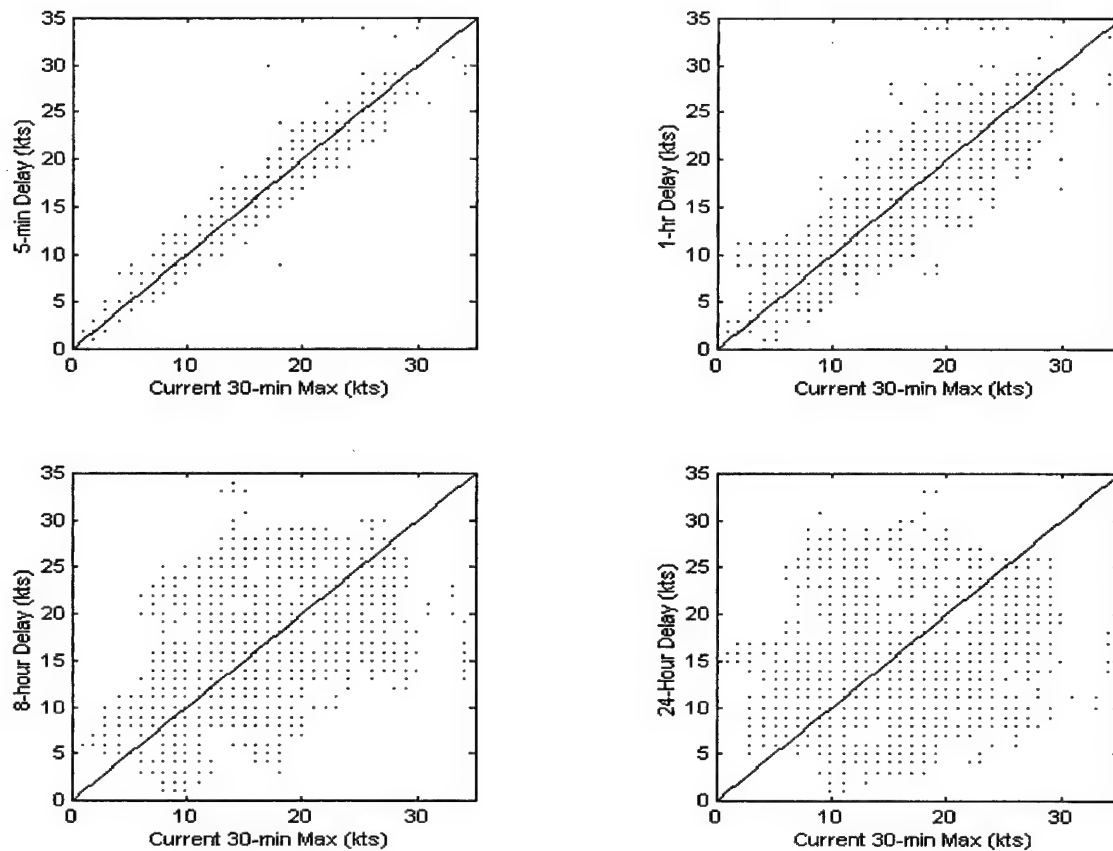


Figure 4.5. Phase Diagrams for 30-minute Maximum Peak Wind Speed. High autocorrelations in the peak wind time series is suggested by the close packing of plots around the diagonals in the top two diagrams (5-minute and 1-hour delays). At longer delays, however, the plots are more widely dispersed from the diagonals, as in the diagrams for 8- and 24-hour delays.

Delays were chosen to correspond with the 1-hour interval associated with the moving averages for all input elements. For example, since the moving averages were computed over 1 hour, the current input was the most recent 1-hour average of the predictor element. The delay 1 input was the 1-hour average from 1 hour ago based on the 13th through the 24th previous data values. Likewise, the delay 2 input was the 1-hour average from 2 hours ago based on the 25th through the 36th previous data values.

Matching delay intervals to the moving average interval made training more efficient and avoided overlaps in the input data and potential redundancies introduced by correlations between different input vectors. Had smaller delay intervals been used, however, they may have improved the network's forecast skill by capturing any higher-frequency signals that may have been present in the data.

4.3 Targets

A neural network adjusts its weights after comparing its outputs to a set of target outputs. For this research the target sets were the 16 observed 30-minute maximum peak wind speeds that occurred starting 30 minutes after the current input time. In other words, the targets show the network the sets of maximum winds that occurred following each set of input conditions. The targets can be viewed as the right answers to the questions posed by the inputs. Following training, the network should generalize well enough to give correct answers (forecasts) to similar but different questions (inputs).

4.4 Network Development

The development phase was a miniature version of the whole process, incorporating network training and testing. (See the file "development.m" in Appendix C for the MATLAB code used in this phase.) The purpose of the development phase was to determine the optimal neural network architecture to use in the training phase.

During development, networks using all possible combinations of 2, 3, ..., 14 neurons and the first, second, and third delays were separately trained on all data periods in Subset 1. Each network configuration could have only one value for its number of neurons (either 2 or 3 or 4, etc.), but for each given number of neurons, a separate

training run was generated for the current input value and the first delay, for the current input value and the first and second delays, and for the current input value and the first, second, and third delays.

Due to prohibitively long processing times (over 5 hours on a 450-MHz processor for some configurations), configurations with 11-14 neurons were limited to 500 training steps. Configurations with 10 or fewer neurons, however, trained for 1,000 steps. The shorter training length for architectures with more neurons was not considered critical, since the objective of the development phase was to simply ascertain somewhat subjectively which architecture was most likely to result in the lowest mean absolute error between network forecasts and observed 30-minute maximum winds.

After each of these development networks was trained on data from a given period, the network was tested on 500 independent inputs from the same data period. "Independent" means the network's training inputs, although drawn from the same period as the test inputs, could not be used again *as* test inputs. The 8,000 (500 x 16) forecasts generated using independent inputs were compared to the 30-minute maximum winds that occurred at the appropriate forecast valid time.

For each period and configuration, the mean absolute error (MAE) between forecasted and observed winds was computed for each of the 16 forecast times ($\frac{1}{2}$, 1, $1\frac{1}{2}$, ..., 8 hours after forecast start time). Finally, the average of the 500 MAEs for each set of 16 forecast valid times was computed. The minimum average MAEs from all valid times determined for each configuration and period are listed in Table 4.2.

Table 4.2. Summary of Development Phase Results

Period	# of Neurons	Min. avg. MAE (kts)	# of Neurons in Configuration with min. avg. MAE	# of Delays in Configuration with min. avg. MAE
2-12 Mar 95	11 - 14	4.76	13	1
2-12 Mar 95	2 - 6	7.89	4	2
2-12 Mar 95	7 - 10	8.76	8	2
19-26 Mar 95	2 - 6	3.98	3	1
19-26 Mar 95	7 - 10	4.78	10	3
19-26 Mar 95	11 - 14	9.39	13	3
5-13 Nov 95	7 - 10	3.75	10	3
5-13 Nov 95	2 - 6	3.79	2	3
5-13 Nov 95	11 - 14	6.90	11	2
24 Nov - 8 Dec 95	7 - 10	3.50	9	3
24 Nov - 8 Dec 95	2 - 6	4.15	3	1
24 Nov - 8 Dec 95	11 - 14	5.03	14	3
11-21 Feb 96	2 - 6	5.73	4	3
11-21 Feb 96	7 - 10	6.10	10	1
11-21 Feb 96	11 - 14	7.49	11	3
15-31 Mar 96	2 - 6	5.12	5	2
15-31 Mar 96	7 - 10	7.67	7	2
15-31 Mar 96	11 - 14	8.90	12	1
14-23 Jan 98	7 - 10	4.51	7	1
14-23 Jan 98	2 - 6	4.68	2	2
14-23 Jan 98	11 - 14	6.88	11	3
30 Nov - 8 Dec 98	11 - 14	2.46	12	3
30 Nov - 8 Dec 98	2 - 6	2.68	3	3
30 Nov - 8 Dec 98	7 - 10	3.11	7	3
12-21 Mar 99	2 - 6	2.41	3	2
12-21 Mar 99	7 - 10	2.44	10	3
12-21 Mar 99	11 - 14	8.35	11	3

Of the 27 network architectures tested, 14 produced minimum average MAEs using all three delays. The lowest average MAEs occurred with 3, 10, and 11 neurons. Based on these results, a network architecture consisting of three delays and 10 neurons was chosen for the training phase, which is described next.

4.5 Network Training

Using the optimal architecture determined in the development phase (10 neurons and 3 delays, each delay containing 12 time steps), a neural network was trained on data from all eight periods in Subset 2 (see the MATLAB files “nntrain3.m” and nnnext.m” in Appendix C).

Approximately the first 85% of input elements from each period were presented to the network for training. Following training on the first data period, the weight/biastable generated was retained and subsequently used as the starting point for the next period’s training. This process continued until all periods in Subset 2 had been used, the network’s weights and biases having received continuous adjustments from one period to the next.

The method of continuous adjustment was deemed reasonable in order to provide the network with a cross section of wintertime conditions and thereby produce a robust neural network with wide operational applicability. As was mentioned earlier, however, the available data periods from the 25 longest continuous periods in the full database were assigned *randomly* to their three subsets. This was done to maintain a balance between thoroughly training on a variety of wind regimes and unfairly biasing the network for success by deliberately choosing training and testing periods containing only certain types of weather conditions.

Each set of inputs was presented to the network for 20 epochs. During training, the mean squared error (MSE) between the network’s internal forecasts and the target values generally started very high, but dropped quickly and settled near the MSE minimum after about 10 epochs. Mean squared error minima were usually in single

digits, representing close fitting of network outputs to the training data. Figure 4.6 shows a typical MSE pattern during network training.

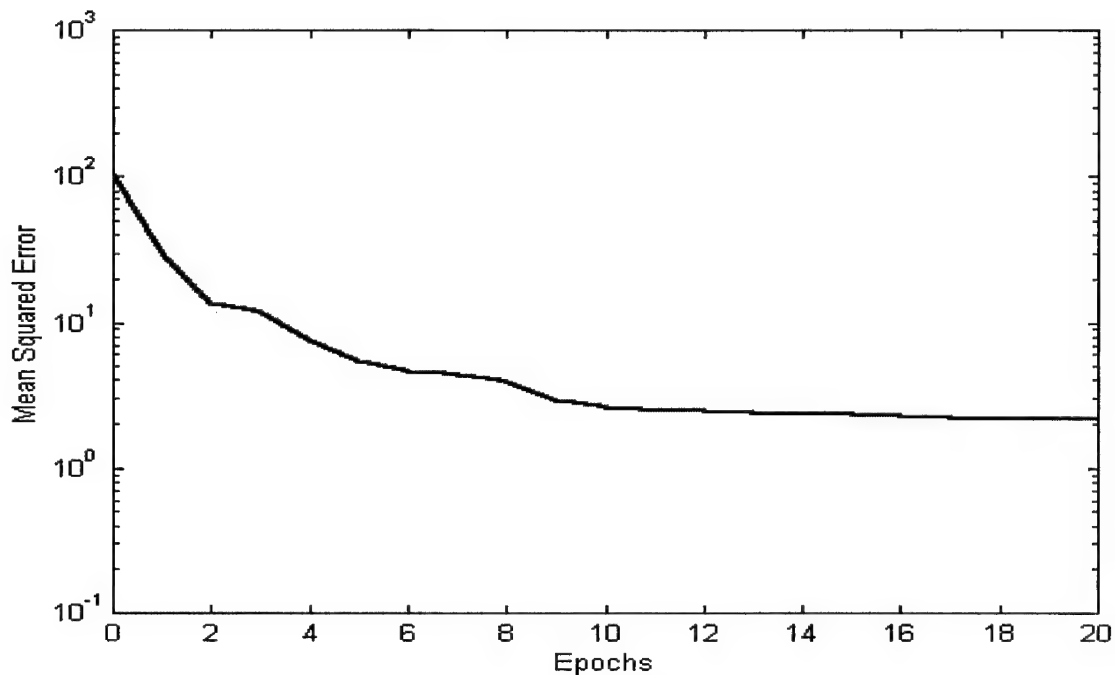


Figure 4.6. Typical Progression of Mean Squared Error (MSE) during Network Training. MSE generally started high (around 100 in this example), but dropped quickly to its minimum (about 2 here) midway through the training session. Note the logarithmic scale on the ordinate axis.

Typically, training should occur over as many as several hundred epochs, but long processing times limited training to only 20 epochs. The decision to use 20 epochs was made after observing that MSE changed less than 0.01 after each epoch beyond 10 or so epochs, only a modest gain in performance.

The result of the training phase was a set of highly adjusted weights and biases, updated after mapping approximately 20,000 input vectors to target outputs over a wide but representative range of conditions.

4.6 Network Testing

During testing, 250 8-hour forecasts were generated for each of the eight periods in Subset 3 using the network trained in the development phase (see the MATLAB file “nnctest.m” in Appendix C). To objectively measure forecast performance, each of the 2,000 forecast start times was chosen randomly.

Three competing forecast options--persistence, climatology, and random values from a climatologically based gamma distribution--were compared to the neural network forecasts. Persistence forecasting assumed the 30-minute maximum peak wind speed at all forecast valid times would be the same as it was at forecast start time. The 30-minute maximum, however, was defined using the 15-minute peak winds before and *after* each forecast valid time. Operationally, the 15-minute winds after the forecast start time would not be known, so persistence forecast values were calculated from the 30-minute period leading up to each forecast start time.

Climatology forecasts assumed the 30-minute maximum peak wind speed at a given forecast valid time would be the mean value for that time of day from the entire database. In order to obtain more representative values, climatological means were computed from the entire period of record, without regard to data gaps. Figure 4.7 shows the 24-hour plot of climatological 30-minute maxima. Compare this figure to Figure 4.2, where the afternoon peak is also evident.

Values for random forecasts were generated from a gamma distribution with $\alpha = 4.9308$ and $\beta = 2.5568$. The gamma distribution was chosen because its shape resembled that of the histogram of 30-minute maximum peak winds from all data subsets (see Figure 4.8).

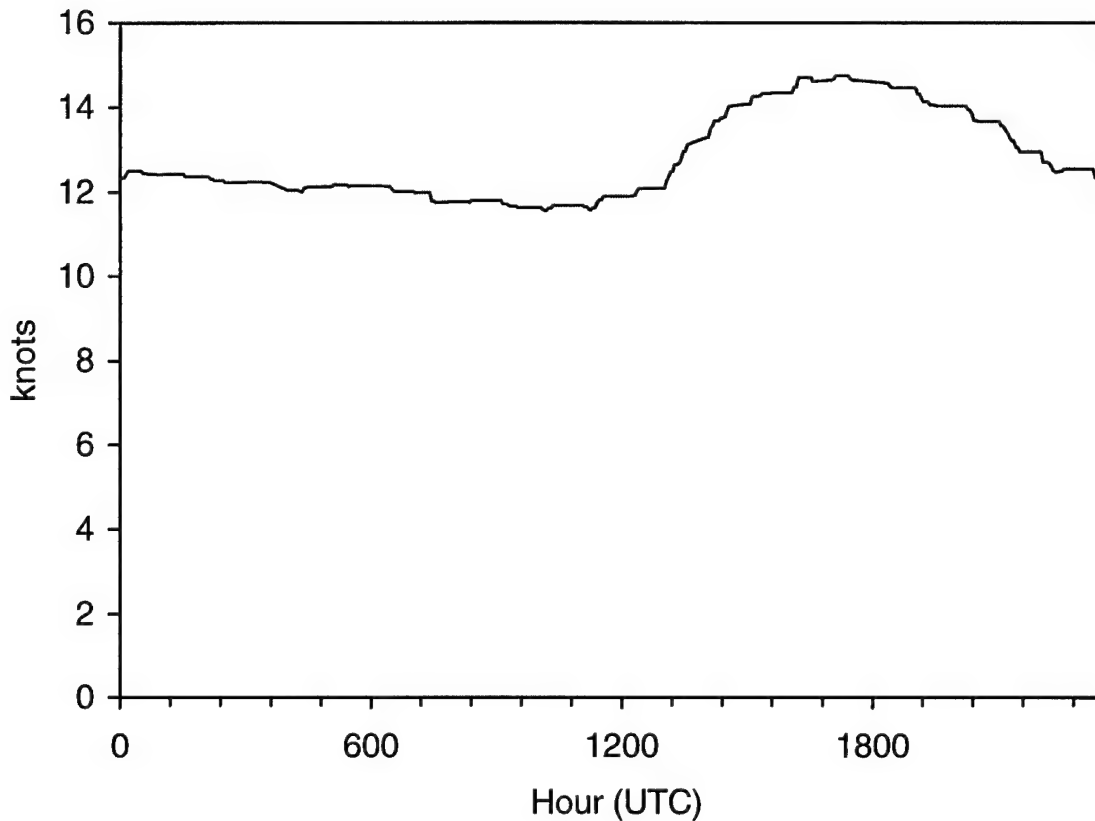


Figure 4.7. Climatological Values of 30-minute Maximum Peak Winds for All Wintertime Observations. Over the 4-year period of record, wintertime maximum winds vary only slightly.

The parameters α and β were computed using the mean μ and variance σ^2 of the maximum wind speeds for the 25 data periods used in this study. For a variable with a gamma distribution (which the maximum winds were assumed to have), the following relations hold: $\mu = \alpha\beta$, and $\sigma^2 = \alpha\beta^2$.

The following measures of forecast performance for the neural network and each of the forecast alternatives were computed: mean absolute error, mean squared error, and maximum error. These errors refer to the differences between the forecasted and observed 30-minute maximum wind.

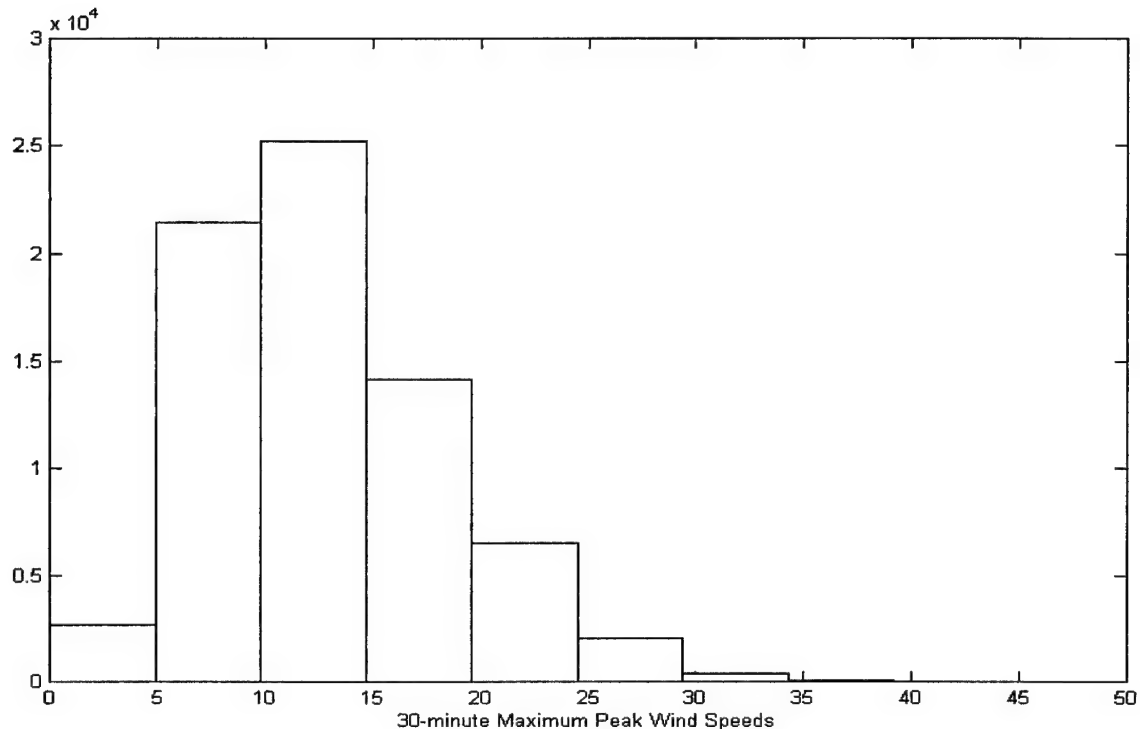


Figure 4.8. Histogram of 30-minute Maximum Peak Wind Speeds for the 25 Data Periods Used. The shape of this distribution was justification for choosing the gamma distribution to generate random forecasts in the testing phase. Wind speeds are in knots.

4.7 Variation on the Original Method

A variation on the training and testing method just described was also developed (see file “nnctest3.m” in Appendix C). In the original method, the randomly generated forecast start times may have placed the forecast period in a weather regime completely unrelated to the regime in effect when the training input data were collected. To see how well the neural network method performed when making predictions near in time to the training data, a separate but identically configured network (10 neurons, 3 delays) for each period in Subsets 2 and 3 was trained and tested.

Each period's network was trained on 1,000 data points (approximately 3½ days) near the beginning of the data period. Training required about 45 minutes per period. After training, each network was tested on 100 sequential forecast start points beginning 50 time steps after the last training point.

4.8 Reliability Intervals

A confidence measure for the neural network forecasts from the previous section was also developed (see file "errsubplots.m" in Appendix C). The 100 MAEs at each valid time for each forecast generated in the variation described above were averaged and their standard deviations were computed. The sum of the average MAE and twice the normalized standard deviation of the MAE formed separate reliability intervals for each of the 16 forecast valid times.

A reliability interval resembles a confidence interval, but it is not a true confidence interval in the strict statistical sense, because the sample MAEs were not distributed normally. Moreover, even if the MAEs had been distributed normally, the confidence/reliability interval with the intervals computed in this study is that of the forecast *accuracy*, not of the forecast itself. Strictly speaking, a confidence interval is an interval of plausible values for the parameter being estimated. This definition implies that the parameter value is unknown, but in this research, the forecast value *is* known; the forecast itself is not being estimated.

What remains unknown, however, is how accurate the given forecast is, i.e., how much does the forecast differ from the observed wind? The reliability intervals computed in this portion of the research represent an attempt to assign high confidence to the neural

network forecasts by determining upper and lower bounds within which the observed maximum wind should fall 95% of the time.

The results of the original neural network training and testing, the variation on the original method, and the reliability interval computations are presented in Chapter 5.

5. Results and Discussion

5.1 Original Method

Mean absolute error (MAE) was the primary measure of forecast skill, since MAE values were in units of knots. Mean squared error (MSE) and maximum error (Max Error) are also included in the following performance data tables, however. Appendix D contains tables for the periods not presented here.

The neural networks developed using the original method performed somewhat worse than persistence overall. Exceptions to this poor performance are found in Tables 5.1 through 5.4, which summarize the performances of the neural networks and each forecasting option. Neural network MAEs were comparable to or less than persistence MAEs for several forecast valid times covered by these tables. The network also frequently had the lowest maximum error of all forecast options during these periods.

During the other forecast periods, the network did not fare as well. In particular, during the two periods in 1996 (Tables 5.5 and 5.6), most network forecasts were worse than random forecasts.

In general, the neural network forecasts worsened later in the forecast period, as did persistence and climatology forecasts. The random forecasts, as one would expect, exhibited no general improvement or worsening with time, however.

The dismal performance of the neural network developed using the original method prompted the change in approach that led to the variation on the original method, the results of which are described next.

Table 5.1. Results from 29 January – 6 February 1997 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	1.39	0.85	4.12	4.46	3.12	1.28	18.88	39.52
1.0	1.51	1.01	4.16	4.44	3.55	1.79	18.92	30.64
1.5	1.53	1.15	4.01	5.06	3.29	1.75	17.30	48.39
2.0	1.69	1.11	4.07	5.41	3.72	1.84	17.68	53.48
2.5	1.81	1.12	4.12	4.44	4.32	2.13	18.06	35.66
3.0	1.87	1.22	4.00	5.34	4.47	2.72	17.04	52.76
3.5	2.05	1.36	3.77	5.05	5.18	3.41	15.08	39.69
4.0	2.25	1.48	3.66	5.07	5.79	3.65	13.93	47.27
4.5	2.42	1.64	3.60	5.06	6.66	4.24	14.01	48.84
5.0	2.76	1.93	3.88	5.21	8.83	5.73	17.39	49.83
5.5	2.85	2.39	4.34	5.63	11.40	8.87	23.64	49.35
6.0	2.81	2.85	4.58	5.45	13.88	11.98	27.71	53.97
6.5	3.26	3.09	5.01	6.75	17.68	13.34	32.19	72.06
7.0	3.56	3.26	5.12	6.15	20.38	14.21	33.26	63.53
7.5	4.24	3.51	5.36	6.81	26.28	15.67	36.05	76.63
8.0	4.75	3.76	5.55	6.64	31.05	17.68	38.19	76.87
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	3.60	2.20	6.58	30.02				
1.0	3.68	3.20	6.46	14.88				
1.5	3.58	3.20	6.14	29.74				
2.0	3.82	4.10	6.04	26.88				
2.5	3.86	4.10	5.96	20.48				
3.0	3.61	3.20	5.67	27.57				
3.5	3.57	4.10	5.29	18.47				
4.0	4.20	4.10	4.96	21.84				
4.5	4.64	4.80	8.50	24.53				
5.0	6.70	5.00	8.45	23.59				
5.5	7.16	7.00	10.65	16.92				
6.0	8.91	7.00	10.42	26.13				
6.5	9.15	7.00	10.61	28.32				
7.0	9.29	7.00	10.54	25.02				
7.5	9.84	8.00	10.53	22.60				
8.0	10.14	8.00	10.48	29.78				

5.2 Variation on the Method

In the variation on the original method, each data period in Subsets 2 and 3 was assigned its own network for training and prediction. This alternate approach produced significantly better results than the original method late in the forecast period.

Table 5.2. Results from 1-10 March 1997 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	2.47	1.31	2.28	4.97	10.41	3.08	7.01	43.04
1.0	3.11	1.86	2.80	5.83	16.76	6.03	11.89	55.49
1.5	3.94	2.55	3.28	5.62	24.86	9.60	17.16	50.17
2.0	4.83	3.26	3.77	5.48	35.16	14.52	23.63	53.24
2.5	5.69	3.96	4.25	6.08	45.62	19.18	29.42	53.13
3.0	6.63	4.57	4.78	6.56	58.29	24.78	35.76	65.11
3.5	7.48	5.04	5.08	7.27	70.05	30.10	38.80	76.42
4.0	8.07	5.35	5.34	6.32	77.82	34.15	41.18	61.60
4.5	8.57	5.76	5.54	7.21	85.24	39.47	42.31	71.57
5.0	8.92	6.12	5.58	6.87	90.68	45.58	41.16	69.33
5.5	9.34	6.33	5.28	7.36	96.24	50.56	36.90	74.47
6.0	9.61	6.69	5.18	7.72	100.06	56.58	34.58	81.89
6.5	9.69	7.01	5.18	7.49	100.22	61.19	32.95	80.06
7.0	9.78	7.30	5.21	7.89	100.73	65.94	31.74	80.99
7.5	9.74	7.47	5.37	8.15	99.58	69.46	32.64	86.35
8.0	9.70	7.62	5.15	8.35	98.38	70.98	29.34	88.24
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	1.13	3.20	2.90	20.47				
1.0	0.85	5.10	2.77	23.56				
1.5	0.62	5.10	2.73	21.99				
2.0	-0.57	4.10	1.79	24.76				
2.5	-0.76	4.10	1.79	10.11				
3.0	-1.00	4.10	1.73	20.10				
3.5	-1.16	4.10	2.00	12.01				
4.0	-1.17	4.10	2.13	13.41				
4.5	-2.36	2.90	1.15	14.13				
5.0	-2.30	2.90	1.57	17.83				
5.5	-5.09	0.00	-0.72	15.43				
6.0	-4.91	0.00	-0.26	16.91				
6.5	-4.67	0.00	0.08	13.96				
7.0	-4.47	-1.00	0.33	10.32				
7.5	-4.30	0.00	0.34	6.11				
8.0	-4.86	-1.00	-1.20	10.69				

A comparison of the tabulated results from each of the two methods shows the strength in the variation. Tables 5.7 through 5.10 summarize testing of the variation method for the periods summarized in Tables 5.1 through 5.4. In three of these periods, nearly all variation method average MAEs for forecast valid times beyond 6.5 hours are

Table 5.3. Results from 2-13 December 1997 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	1.98	2.03	2.19	5.67	7.09	7.49	8.51	53.26
1.0	2.06	2.04	2.30	5.52	7.75	10.65	8.98	45.97
1.5	1.92	2.42	2.32	4.98	6.40	13.06	8.92	36.20
2.0	2.07	2.81	2.63	5.29	6.85	16.13	10.86	49.83
2.5	2.30	3.03	2.81	4.75	8.13	20.03	11.87	38.01
3.0	2.54	3.09	3.12	4.53	11.05	21.21	13.64	34.35
3.5	3.20	2.73	3.59	5.62	15.00	13.89	17.17	50.74
4.0	3.62	2.77	4.04	5.40	17.44	11.88	21.30	53.43
4.5	3.70	2.80	4.61	5.13	18.56	13.23	27.45	42.39
5.0	3.67	2.94	4.90	5.74	18.14	12.62	30.48	56.58
5.5	3.29	3.04	5.32	5.47	15.22	13.48	35.44	47.29
6.0	3.18	3.20	5.48	6.17	13.27	14.95	37.23	61.37
6.5	3.40	3.51	5.91	5.02	14.52	15.77	42.66	44.68
7.0	3.52	3.02	6.07	6.00	15.04	13.34	44.77	56.01
7.5	3.55	2.68	5.86	5.47	15.27	10.35	40.93	60.10
8.0	4.00	3.25	5.91	5.32	19.87	14.11	42.04	47.39
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	8.28	7.00	8.66	24.43				
1.0	8.51	8.20	8.79	19.25				
1.5	8.68	6.00	8.75	12.68				
2.0	6.43	8.20	8.92	27.12				
2.5	7.76	7.00	9.00	18.97				
3.0	8.71	7.00	9.18	19.00				
3.5	8.67	7.00	9.59	21.88				
4.0	8.85	8.20	10.06	25.02				
4.5	8.87	8.20	10.66	14.90				
5.0	6.81	7.00	10.87	22.08				
5.5	6.16	8.20	11.36	21.02				
6.0	6.19	8.20	11.43	22.38				
6.5	6.50	7.00	11.58	23.10				
7.0	6.63	8.20	11.80	31.00				
7.5	6.64	6.10	9.65	36.56				
8.0	9.77	6.10	12.77	19.98				

lower than the original method MAEs. All 8-hour average MAEs for the variation are lower than the original method MAEs.

For 11 of the 16 variation method test periods, neural net forecasts late in the forecast period are more accurate than neural net forecasts early in the period. This

Table 5.4. Results from 25 January – 4 February 1999 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	4.37	2.02	3.02	4.79	26.56	7.58	11.12	34.55
1.0	4.55	2.45	3.42	5.54	27.70	9.50	13.84	44.88
1.5	4.65	3.02	3.83	5.51	28.20	15.51	16.51	42.97
2.0	4.42	3.58	3.96	6.41	26.61	21.75	17.36	64.03
2.5	4.33	4.46	4.30	6.08	25.88	28.85	20.63	49.17
3.0	4.41	5.34	4.72	6.41	27.06	38.63	27.77	60.79
3.5	4.14	5.91	4.88	5.23	24.51	49.25	29.86	44.70
4.0	3.67	6.29	4.87	5.60	20.30	58.81	29.66	49.20
4.5	3.25	6.66	4.88	6.52	17.64	61.05	29.70	65.74
5.0	2.81	6.89	4.60	6.01	13.45	64.65	27.38	62.93
5.5	2.62	7.08	4.37	6.57	11.79	67.49	25.82	69.50
6.0	2.62	7.09	4.15	5.60	11.46	67.75	24.68	57.38
6.5	2.77	7.01	4.09	5.91	12.05	65.63	24.49	66.09
7.0	2.72	6.58	3.80	6.23	11.63	61.51	22.23	69.56
7.5	2.89	6.68	3.75	5.72	12.87	60.41	22.26	62.37
8.0	3.16	6.73	3.71	6.05	15.17	58.40	22.22	61.77
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	3.03	8.00	5.96	16.45				
1.0	2.75	8.00	5.68	20.71				
1.5	3.52	9.90	6.49	16.82				
2.0	3.33	9.90	6.55	26.97				
2.5	5.04	10.90	8.22	13.73				
3.0	8.90	10.90	12.51	18.21				
3.5	8.74	14.00	12.51	26.55				
4.0	8.73	16.90	12.43	17.89				
4.5	8.74	15.00	12.43	28.48				
5.0	8.80	16.90	12.31	23.90				
5.5	8.91	16.90	12.23	22.38				
6.0	9.09	18.10	12.24	31.89				
6.5	9.33	18.10	12.24	31.21				
7.0	9.53	16.90	12.04	23.31				
7.5	9.70	16.90	12.13	27.78				
8.0	9.87	16.90	12.18	23.92				

network skill late in the forecast period also manifests itself in eight of the periods examined, where the variation's neural net MAE is less than that of a persistence forecast for the last two to four forecast valid times (for instance, see Tables 5.7 and 5.9 through 5.15). Appendix D contains performance data tables for the periods not presented here.

Table 5.5. Results from 23 February – 7 March 1996 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persistence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persistence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	8.11	0.81	10.86	10.56	66.21	1.14	118.44	133.65
1.0	9.25	0.89	11.02	10.13	85.97	1.25	121.84	125.27
1.5	10.33	0.81	10.85	10.57	107.27	0.99	118.26	132.47
2.0	9.26	0.86	10.77	11.25	86.34	1.30	116.72	144.75
2.5	9.10	0.71	10.56	10.20	83.57	1.26	112.28	127.35
3.0	9.43	0.67	10.52	9.46	89.58	1.19	111.29	111.59
3.5	10.21	0.80	10.29	10.18	104.93	1.16	106.65	122.03
4.0	10.78	1.22	9.78	10.32	117.04	1.97	96.56	126.60
4.5	11.79	1.01	9.13	9.78	139.87	1.75	84.19	119.86
5.0	12.79	1.01	8.47	9.91	164.36	1.86	72.64	123.33
5.5	14.08	1.00	8.15	9.82	199.04	1.99	67.26	118.85
6.0	15.84	1.15	7.64	10.04	251.68	2.12	59.26	121.99
6.5	16.53	1.00	7.63	9.76	274.29	1.67	59.15	119.48
7.0	16.99	1.03	7.48	9.87	289.56	1.63	56.87	119.54
7.5	16.76	1.15	7.31	10.05	282.26	2.10	54.67	125.99
8.0	15.08	1.27	7.45	9.37	229.50	2.62	57.54	114.81
Forecast Valid Time	Neural Net Max Error (kts)	Persistence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	-6.57	1.90	-9.33	7.74				
1.0	-7.67	1.90	-9.44	9.27				
1.5	-8.79	1.90	-9.31	6.36				
2.0	-6.84	2.90	-8.35	3.05				
2.5	-6.72	2.90	-8.18	11.60				
3.0	-7.01	3.90	-8.10	4.05				
3.5	-7.84	2.00	-7.92	13.17				
4.0	-8.51	2.90	-7.51	6.25				
4.5	-9.70	2.90	-7.04	5.56				
5.0	-10.75	3.90	-6.44	3.80				
5.5	-12.16	2.90	-6.23	16.88				
6.0	-13.94	3.90	-5.74	10.38				
6.5	-14.58	2.90	-5.67	7.39				
7.0	-15.03	2.90	-5.52	12.28				
7.5	-14.76	3.90	-5.30	6.70				
8.0	-12.89	3.90	-5.25	5.79				

Figure 5.1 shows Subset 3 summary MAE results for both the original and variation methods as well as persistence MAEs for both methods. The plots were calculated by averaging each method's MAEs for each forecast valid time over all periods in data Subset 3. The original method's MAEs and both persistence forecast

Table 5.6. Results from 24 November – 8 December 1996 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persistence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persistence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	10.20	1.44	7.86	8.69	114.80	3.14	72.80	99.41
1.0	10.78	2.11	8.22	9.25	127.54	5.92	78.83	114.52
1.5	11.25	2.69	8.41	9.50	137.23	9.31	81.27	116.35
2.0	11.73	3.12	8.80	9.15	146.87	13.48	86.43	107.08
2.5	12.24	3.62	9.22	9.17	157.79	16.63	92.34	103.51
3.0	12.61	4.06	9.41	9.47	166.24	20.72	94.86	117.85
3.5	12.98	4.28	9.57	9.97	174.32	24.76	96.85	123.47
4.0	13.30	4.22	10.06	9.36	180.82	26.26	105.16	117.95
4.5	13.49	4.19	10.27	9.16	185.65	26.31	109.08	110.82
5.0	13.57	4.27	10.26	11.47	187.60	26.44	108.71	163.30
5.5	13.48	4.31	10.18	10.15	185.05	25.40	107.12	124.20
6.0	13.25	4.10	10.10	10.55	179.24	23.91	105.56	134.51
6.5	12.90	4.04	9.97	10.10	170.33	23.10	103.17	129.05
7.0	12.53	3.79	9.91	9.90	160.83	19.55	101.43	122.24
7.5	12.02	3.65	9.60	9.54	146.94	16.05	94.43	116.22
8.0	11.61	3.46	9.62	9.65	136.65	14.49	94.39	115.31
Forecast Valid Time	Neural Net Max Error (kts)	Persistence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	-4.97	3.10	-2.49	14.78				
1.0	-5.25	4.10	-2.59	11.14				
1.5	-5.48	5.00	-2.57	14.01				
2.0	-5.67	6.00	-2.62	8.23				
2.5	-6.72	5.10	-4.62	4.07				
3.0	-6.11	6.00	-4.67	9.18				
3.5	-7.84	7.90	-4.66	20.48				
4.0	-9.37	7.00	-6.06	12.33				
4.5	-9.36	6.00	-6.10	12.86				
5.0	-9.30	5.10	-5.97	11.20				
5.5	-9.19	4.80	-5.92	7.30				
6.0	-9.01	6.90	-5.95	4.99				
6.5	-8.77	6.00	-5.96	8.76				
7.0	-8.57	6.00	-6.08	11.27				
7.5	-8.40	5.10	-6.11	8.98				
8.0	-8.23	6.00	-6.33	11.93				

MAEs steadily rise from the beginning of the forecast period. The variation method's MAEs, however, after rising for the first three forecast valid times, show an almost continuous decline until the end of the forecast period. At 6.5 hours and beyond,

Table 5.7. Results from 29 January - 6 February 1997 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persistence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persistence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	5.89	1.89	6.68	7.09	44.31	5.65	47.80	81.01
1.0	6.97	2.19	6.57	7.27	61.25	7.04	46.18	87.61
1.5	6.00	2.21	6.38	8.49	45.85	6.36	44.66	97.51
2.0	2.95	2.30	6.10	7.88	12.89	6.87	42.23	100.90
2.5	1.54	2.62	6.13	7.08	3.97	9.24	42.63	79.21
3.0	1.61	2.94	6.08	6.83	3.98	12.60	42.07	77.78
3.5	3.00	2.84	6.23	7.28	12.56	13.13	43.93	78.84
4.0	4.58	2.54	6.11	7.12	27.31	10.35	42.14	84.90
4.5	5.11	2.37	6.08	6.38	32.58	9.65	40.90	71.82
5.0	5.82	2.42	6.47	6.78	38.82	11.78	44.99	72.97
5.5	6.31	2.50	7.22	6.63	43.19	11.62	55.17	72.43
6.0	4.85	2.18	7.59	6.41	26.80	8.93	60.63	64.62
6.5	1.87	2.09	7.77	6.82	5.78	6.93	62.59	74.72
7.0	3.06	2.12	7.81	5.88	11.01	6.65	62.94	62.39
7.5	3.56	2.11	7.80	6.63	14.82	6.75	62.74	68.41
8.0	1.90	1.98	8.16	7.66	4.75	5.69	68.44	90.12
Forecast Valid Time	Neural Net Max Error (kts)	Persistence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	12.22	5.10	9.90	27.71				
1.0	13.82	5.10	9.77	32.11				
1.5	12.50	4.10	9.73	21.37				
2.0	7.65	4.10	9.72	28.21				
2.5	3.85	5.10	9.79	26.63				
3.0	3.76	6.10	9.73	26.88				
3.5	7.21	6.10	10.00	27.60				
4.0	10.61	6.10	10.02	32.93				
4.5	11.14	5.10	10.19	24.09				
5.0	11.26	5.10	10.75	25.09				
5.5	10.56	6.10	11.38	31.63				
6.0	9.42	6.10	11.78	21.06				
6.5	7.85	4.10	11.18	25.33				
7.0	5.46	2.00	9.17	23.38				
7.5	5.05	2.00	9.24	21.47				
8.0	5.28	2.00	9.60	34.85				

the variation neural net MAEs nearly equal the persistence MAEs, and at some points are even lower than the persistence MAEs computed during testing of the original method.

Table 5.8. Results from 1-10 March 1997 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	2.77	1.10	1.77	4.54	10.59	2.07	4.16	33.42
1.0	3.00	1.42	1.65	4.87	11.58	2.93	3.77	41.22
1.5	3.74	1.56	1.42	4.51	15.01	3.75	2.96	30.24
2.0	4.33	1.48	1.25	4.73	21.17	3.60	2.38	32.23
2.5	4.31	1.24	1.12	5.09	23.59	2.63	2.02	37.63
3.0	4.66	0.98	0.96	4.84	30.08	1.86	1.64	34.94
3.5	5.18	0.94	0.93	4.97	36.85	1.41	1.51	38.48
4.0	5.89	1.11	0.93	4.83	43.99	1.82	1.23	37.03
4.5	6.66	1.26	0.95	4.87	50.68	2.41	1.19	32.57
5.0	6.40	1.53	1.15	4.82	45.68	3.26	1.82	35.31
5.5	5.18	1.61	1.46	5.22	29.56	3.58	2.70	41.88
6.0	3.60	1.83	1.88	4.89	14.65	4.91	4.40	36.78
6.5	3.10	2.25	2.03	4.88	11.21	7.57	5.78	35.44
7.0	3.45	2.56	2.36	4.24	13.73	10.66	7.60	27.52
7.5	3.62	2.90	2.57	4.85	15.34	14.20	9.11	38.76
8.0	3.77	3.32	2.79	5.29	16.05	16.87	10.86	44.18
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	0.84	2.90	3.65	16.78				
1.0	0.16	3.90	3.65	22.31				
1.5	-1.46	3.90	3.50	13.88				
2.0	-1.59	3.90	3.40	13.26				
2.5	-0.84	2.90	3.22	20.19				
3.0	-0.89	2.00	2.96	19.03				
3.5	0.47	2.00	2.94	21.01				
4.0	1.41	1.00	2.60	19.00				
4.5	3.10	1.00	2.46	8.35				
5.0	1.65	2.00	0.96	17.33				
5.5	-0.36	2.90	0.61	18.80				
6.0	0.45	5.10	5.47	19.68				
6.5	1.73	7.00	5.55	20.16				
7.0	3.03	7.00	5.31	13.86				
7.5	2.94	8.00	5.34	23.45				
8.0	3.90	8.00	5.51	20.84				

Figures 5.2 through 5.17 show representative plots of the results of testing the networks trained with the variation on the original method. The plots show 100 forecasts for the indicated forecast valid times and provide a sense of how well the networks

Table 5.9. Results from 2-13 December 1997 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persistence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persistence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	3.67	1.99	3.61	4.35	18.99	8.63	19.36	30.29
1.0	3.99	2.35	3.92	5.70	20.19	10.76	21.81	47.01
1.5	4.69	2.49	4.15	6.11	28.80	12.08	24.08	54.21
2.0	5.40	2.64	4.59	5.40	38.06	12.99	27.98	40.49
2.5	5.22	2.88	4.58	5.79	36.12	12.15	26.90	48.17
3.0	4.74	2.72	4.92	5.84	29.37	10.34	29.01	47.49
3.5	3.95	2.93	4.96	6.04	20.75	12.09	28.63	50.67
4.0	3.46	3.14	4.63	6.89	15.07	13.50	24.83	61.28
4.5	3.12	2.96	3.91	5.52	12.17	11.57	18.08	44.23
5.0	2.79	3.01	3.18	6.34	9.82	11.92	12.81	55.15
5.5	2.86	3.38	3.03	6.61	10.68	16.67	11.55	62.73
6.0	2.20	3.93	3.10	6.66	8.48	21.50	12.09	61.82
6.5	2.16	3.99	3.07	6.55	7.28	20.48	11.92	60.03
7.0	3.21	4.19	2.88	5.53	12.29	21.40	10.76	43.66
7.5	3.96	4.05	2.89	6.00	18.02	19.98	10.95	51.94
8.0	3.90	3.85	2.74	5.37	18.96	18.72	10.10	49.01
Forecast Valid Time	Neural Net Max Error (kts)	Persistence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	8.05	7.00	0.53	18.51				
1.0	8.20	6.00	0.52	15.32				
1.5	9.43	6.00	0.59	19.37				
2.0	11.46	6.00	0.47	12.92				
2.5	10.25	6.00	-0.20	11.76				
3.0	8.32	5.10	-0.18	21.65				
3.5	7.09	4.10	-1.91	14.28				
4.0	5.73	4.10	-1.35	10.91				
4.5	4.18	4.10	-0.88	13.52				
5.0	3.46	7.00	1.58	13.93				
5.5	5.11	10.20	5.13	24.41				
6.0	5.42	10.20	5.36	14.88				
6.5	5.86	8.00	5.43	27.15				
7.0	6.02	6.10	5.80	8.79				
7.5	6.18	6.10	5.71	23.18				
8.0	4.35	6.10	5.85	22.77				

forecasted with various lead times. The plots presented here are only a portion of those generated for this research. Plots for all 16 forecast valid times for all data periods in Subset 2 are available from the author.

Table 5.10. Results from 25 January - 4 February 1999 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persistence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persistence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	3.63	2.28	2.68	5.33	16.77	9.58	13.48	49.74
1.0	4.00	3.12	2.14	5.34	21.23	15.16	6.73	51.19
1.5	5.09	3.39	2.06	4.48	35.25	18.29	5.60	35.74
2.0	5.58	2.99	2.01	4.51	45.97	17.16	5.30	38.62
2.5	5.61	2.71	2.15	5.27	43.54	17.03	6.25	45.66
3.0	4.91	2.74	2.25	5.11	33.56	16.33	6.81	47.49
3.5	5.57	3.14	2.40	5.45	41.14	18.50	7.84	53.46
4.0	6.89	3.45	2.90	4.47	53.76	23.43	10.87	35.76
4.5	6.73	3.52	3.44	5.30	50.83	27.49	14.92	46.13
5.0	3.87	3.27	4.16	4.57	21.42	26.15	20.34	31.90
5.5	5.40	3.14	4.58	4.81	32.85	22.09	23.63	37.97
6.0	9.82	3.08	4.94	5.50	121.30	17.78	26.45	56.61
6.5	9.61	3.34	4.96	5.01	112.17	17.97	26.65	43.81
7.0	5.26	3.33	5.27	4.65	33.03	20.75	29.88	45.09
7.5	2.29	3.06	5.13	5.97	6.82	22.11	28.34	59.95
8.0	2.51	2.91	5.12	5.08	7.77	21.29	28.46	44.68
Forecast Valid Time	Neural Net Max Error (kts)	Persistence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	6.47	5.00	11.63	20.30				
1.0	2.67	4.10	8.72	24.91				
1.5	2.70	6.00	5.69	19.06				
2.0	1.04	5.10	5.57	27.31				
2.5	2.12	4.10	5.90	16.88				
3.0	3.56	3.20	5.92	23.98				
3.5	5.24	5.00	6.09	23.44				
4.0	6.89	5.10	5.65	18.57				
4.5	8.55	5.10	6.12	19.63				
5.0	8.65	5.00	6.68	13.78				
5.5	8.42	4.10	7.03	18.19				
6.0	16.97	6.00	7.26	21.04				
6.5	16.53	6.00	7.33	17.61				
7.0	9.08	6.00	7.70	25.86				
7.5	4.55	5.10	7.61	23.22				
8.0	4.81	3.20	7.75	23.76				

The forecast plots in Figures 5.2 through 5.17 support the conclusion drawn earlier: The variation method shows skill late in the forecast period. Through 5 hours (Figures 5.2 through 5.11), the neural net plots are unimpressive. In many of these early

Table 5.11. Results from 5-13 December 1995 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	8.08	2.15	3.43	5.63	78.70	6.65	19.36	51.70
1.0	6.68	2.60	3.34	5.15	55.06	10.90	18.26	41.28
1.5	6.79	2.78	3.15	5.64	53.98	12.97	15.87	56.26
2.0	7.69	2.93	3.09	6.13	67.80	14.76	15.20	63.71
2.5	8.37	3.71	3.19	5.11	81.40	18.95	16.63	45.90
3.0	7.64	4.30	3.40	5.09	70.72	23.69	18.41	37.33
3.5	6.43	4.74	3.49	5.63	52.84	27.22	18.99	60.29
4.0	4.97	4.99	3.87	5.05	32.84	29.33	20.78	43.99
4.5	3.29	4.90	3.98	5.70	14.63	29.46	21.31	56.25
5.0	2.94	4.64	4.67	5.21	12.08	26.40	27.41	45.09
5.5	3.13	4.30	4.97	5.17	13.22	23.28	30.16	44.45
6.0	1.76	3.91	5.28	5.52	4.04	20.86	32.92	52.30
6.5	1.95	3.31	5.68	4.81	7.09	18.03	36.55	41.94
7.0	1.87	3.19	5.86	5.95	6.38	16.86	38.54	53.84
7.5	1.53	3.16	6.09	6.31	4.10	14.80	40.87	75.34
8.0	1.94	3.05	6.30	6.24	5.33	12.31	42.25	65.62
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	16.34	6.00	9.79	22.21				
1.0	14.04	6.00	9.75	17.05				
1.5	12.58	6.00	8.92	25.89				
2.0	12.61	6.00	7.80	24.49				
2.5	14.95	7.00	7.98	22.01				
3.0	15.68	7.00	8.39	14.46				
3.5	12.65	6.00	8.86	29.25				
4.0	9.18	7.00	7.56	17.92				
4.5	6.58	7.00	7.77	26.99				
5.0	6.23	6.10	8.26	19.94				
5.5	6.44	6.10	8.33	25.91				
6.0	3.59	5.00	8.48	21.46				
6.5	0.36	6.00	8.70	20.72				
7.0	0.52	6.00	8.75	22.61				
7.5	1.79	7.00	8.67	38.70				
8.0	4.41	6.10	8.60	19.96				

plots, the traces of network forecasts appear to wander aimlessly, with no inclination to match the verification line.

Table 5.12. Results from 23 February – 7 March 1996 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	4.62	0.71	2.80	4.60	27.24	1.33	10.27	38.06
1.0	4.90	0.94	2.51	5.19	29.07	1.85	8.44	48.99
1.5	6.40	1.30	2.23	4.38	60.97	2.91	6.91	32.45
2.0	3.10	1.73	1.99	4.38	12.27	4.64	5.98	31.73
2.5	2.90	2.08	1.75	4.99	10.09	6.65	4.81	40.04
3.0	2.47	2.55	1.84	5.06	8.24	9.27	5.99	39.26
3.5	4.23	3.06	2.11	5.53	30.73	12.76	8.41	47.84
4.0	4.06	3.51	2.18	5.50	24.90	15.69	9.11	55.49
4.5	2.85	3.83	2.37	4.81	11.97	17.96	10.58	35.89
5.0	3.46	3.89	2.64	5.27	18.18	18.72	12.31	50.52
5.5	3.00	3.72	2.74	5.83	14.83	18.18	12.42	59.23
6.0	2.49	3.51	2.83	5.19	9.85	16.61	12.70	49.15
6.5	2.18	3.24	2.86	4.75	7.44	14.33	12.58	36.04
7.0	2.18	3.09	2.91	4.91	7.97	12.23	12.68	38.70
7.5	2.67	2.89	2.95	4.78	9.74	10.35	12.74	43.51
8.0	2.78	2.86	3.19	5.35	10.40	9.79	13.85	45.79
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	7.50	1.90	5.14	19.88				
1.0	8.95	1.90	4.94	25.21				
1.5	16.63	3.20	4.66	14.78				
2.0	8.52	4.10	4.32	16.95				
2.5	4.84	5.10	4.71	22.19				
3.0	4.37	6.10	6.47	19.64				
3.5	6.23	8.00	7.45	22.01				
4.0	5.71	8.00	7.21	28.00				
4.5	7.19	8.90	7.24	16.60				
5.0	8.37	7.90	7.41	26.33				
5.5	8.28	7.90	7.32	24.90				
6.0	7.17	7.00	7.33	25.78				
6.5	7.52	7.90	7.28	25.26				
7.0	7.32	6.00	7.18	17.86				
7.5	7.09	6.00	7.14	21.55				
8.0	6.34	5.10	7.14	20.73				

Starting with the 5.5-hour forecast (Figure 5.12), however, an improvement is evident, and most of the neural network forecasts follow the verification line. Where persistence produces a better forecast than the neural net, overall neural net MAEs are

Table 5.13. Results from 24 November – 8 December 1996 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	2.96	1.38	3.66	5.67	10.44	2.81	14.97	44.98
1.0	2.55	1.68	3.89	6.77	7.89	4.25	16.75	60.70
1.5	3.67	1.83	4.32	6.48	15.33	5.38	20.82	57.08
2.0	4.52	2.22	4.96	6.40	24.21	7.58	27.88	54.97
2.5	4.03	2.56	5.81	7.27	20.63	9.26	38.20	70.85
3.0	3.97	2.89	6.45	6.94	19.46	13.38	48.18	68.50
3.5	3.86	2.98	6.86	7.52	17.96	17.14	56.16	80.35
4.0	2.72	3.06	7.58	8.62	12.98	18.94	67.57	101.06
4.5	2.91	3.53	7.80	7.98	13.79	21.97	71.46	87.54
5.0	3.63	3.95	7.90	8.94	19.47	24.71	73.67	107.99
5.5	3.52	4.22	8.24	8.89	20.07	25.83	79.10	103.13
6.0	3.36	4.42	8.45	8.98	15.57	25.55	81.80	112.18
6.5	2.96	4.58	8.87	10.19	12.12	25.35	87.29	124.45
7.0	3.25	4.66	9.24	9.39	13.67	25.35	92.59	115.35
7.5	4.39	4.55	9.42	9.76	23.96	24.91	94.93	122.34
8.0	5.20	4.36	9.61	9.40	31.30	24.10	97.23	112.29
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo MaxError (kts)	Random Max Error (kts)				
0.5	5.72	3.10	-0.96	11.51				
1.0	5.38	4.10	-1.16	14.45				
1.5	6.76	4.10	-1.44	16.06				
2.0	8.17	4.10	-1.78	7.82				
2.5	7.78	3.20	-2.29	9.86				
3.0	7.45	5.10	-2.53	17.55				
3.5	6.57	5.10	-2.45	7.68				
4.0	4.17	1.90	-2.69	6.19				
4.5	2.42	3.10	-2.66	15.72				
5.0	1.20	4.10	-2.49	12.03				
5.5	1.77	6.00	-2.58	11.61				
6.0	3.38	6.00	-2.57	11.86				
6.5	4.81	4.10	-2.62	16.05				
7.0	2.54	4.10	-4.62	3.03				
7.5	0.72	4.10	-4.66	12.08				
8.0	0.01	2.90	-4.66	15.77				

generally closer to persistence MAEs than earlier in the forecast period. Interestingly, although the neural net predicted negative wind speeds for some of the 7-hour forecasts (Figure 5.15), the difference between persistence and neural net MAE for this forecast

Table 5.14. Results from 14-23 January 1999 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	9.77	0.84	5.08	7.28	96.56	1.38	26.87	74.17
1.0	11.72	1.24	5.05	7.46	140.35	3.08	27.36	73.48
1.5	9.91	1.64	5.05	6.86	105.12	5.48	28.60	62.48
2.0	7.68	2.10	5.02	6.26	69.81	8.46	29.49	55.28
2.5	6.45	2.67	5.11	7.12	52.08	12.09	31.63	71.47
3.0	6.76	2.89	4.96	7.00	58.75	14.82	31.46	67.15
3.5	8.99	3.01	4.59	7.39	99.46	16.41	28.93	77.88
4.0	10.81	3.09	4.50	6.05	136.62	17.58	29.15	52.25
4.5	10.41	3.34	4.17	6.63	124.05	18.96	26.90	64.83
5.0	9.29	3.49	3.71	5.89	98.21	20.06	23.70	46.24
5.5	8.49	3.77	3.48	6.06	81.64	22.15	22.41	52.69
6.0	7.78	4.05	3.16	5.63	69.17	23.21	19.68	48.29
6.5	7.35	4.40	2.86	5.52	63.25	24.83	16.97	54.31
7.0	5.84	4.76	2.47	5.61	43.27	27.98	13.61	47.91
7.5	2.19	5.08	1.99	4.57	10.13	31.42	9.48	34.38
8.0	2.35	5.59	1.64	5.72	7.02	35.91	6.45	48.46
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	-6.61	1.90	-4.06	6.74				
1.0	-5.02	6.00	-0.16	14.58				
1.5	-2.51	6.00	-0.44	11.53				
2.0	1.20	7.00	0.22	9.93				
2.5	3.95	7.90	0.61	14.70				
3.0	2.39	8.90	0.37	12.79				
3.5	-0.56	8.90	0.45	32.53				
4.0	-2.58	8.00	0.21	13.01				
4.5	-3.56	8.00	0.24	13.53				
5.0	-3.10	8.00	0.41	12.13				
5.5	-4.08	8.00	0.32	11.07				
6.0	-3.46	8.90	0.33	19.08				
6.5	-3.39	8.90	0.28	30.38				
7.0	-2.59	7.90	0.18	18.89				
7.5	2.05	8.90	0.14	14.75				
8.0	4.31	10.10	2.34	20.20				

valid time appears to be among the smallest of all the valid times. At 6, 7.5, and 8 hours (Figures 5.13, 5.16, and 5.17), overall neural net MAEs are less than persistence MAEs.

Table 5.15. Results from 21-31 March 1999 (Variation).

Forecast Valid Time	Neural Net MAE (kts)	Persistence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persistence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	8.55	1.61	1.23	5.02	77.03	4.66	2.43	39.45
1.0	5.74	2.33	1.25	4.61	41.89	8.56	2.68	31.94
1.5	4.26	2.83	1.73	4.82	24.55	14.11	6.21	35.57
2.0	5.22	2.95	2.05	5.43	41.99	16.31	7.96	44.62
2.5	7.00	3.00	2.54	5.21	75.68	16.23	10.99	48.27
3.0	8.89	3.23	2.58	3.84	113.75	16.59	11.31	23.74
3.5	9.39	3.12	2.61	4.97	110.50	14.47	11.62	38.40
4.0	8.36	3.07	2.67	4.41	80.52	14.51	11.97	32.07
4.5	6.76	3.08	2.78	4.53	54.93	15.01	12.37	33.22
5.0	5.79	3.27	2.85	4.81	45.64	15.30	12.35	37.14
5.5	4.83	3.55	2.73	5.61	31.08	16.73	11.07	47.90
6.0	3.82	3.75	2.77	5.01	18.64	18.90	10.95	45.87
6.5	2.76	3.56	2.81	4.41	10.02	18.60	11.07	32.14
7.0	2.21	3.50	2.57	5.12	7.51	18.33	9.43	42.38
7.5	2.76	3.30	2.40	4.35	12.63	16.09	8.35	32.97
8.0	4.22	3.00	2.05	4.43	27.00	12.47	6.55	26.57
	Neural Net Max Error (kts)	Persistence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	13.11	4.80	4.78	20.62				
1.0	14.05	6.00	5.92	17.76				
1.5	11.49	9.90	8.26	15.37				
2.0	7.87	9.90	8.33	17.18				
2.5	4.96	9.00	8.70	28.99				
3.0	2.05	9.00	8.70	15.16				
3.5	-1.10	8.00	8.75	21.28				
4.0	-2.45	7.00	8.63	15.71				
4.5	1.16	8.00	8.59	18.21				
5.0	3.67	8.00	8.46	23.04				
5.5	7.05	6.10	8.14	20.05				
6.0	9.65	7.00	8.04	22.61				
6.5	6.96	8.00	8.04	20.42				
7.0	6.43	8.00	7.67	19.23				
7.5	8.99	8.00	7.40	24.09				
8.0	12.44	7.00	6.96	11.02				

This apparent skill of the neural network in forecasting for long lead times represents a potential enhancement to Launch Weather Officers' current forecast process. Persistence generally outperforms other methods for short lead times, so the neural net

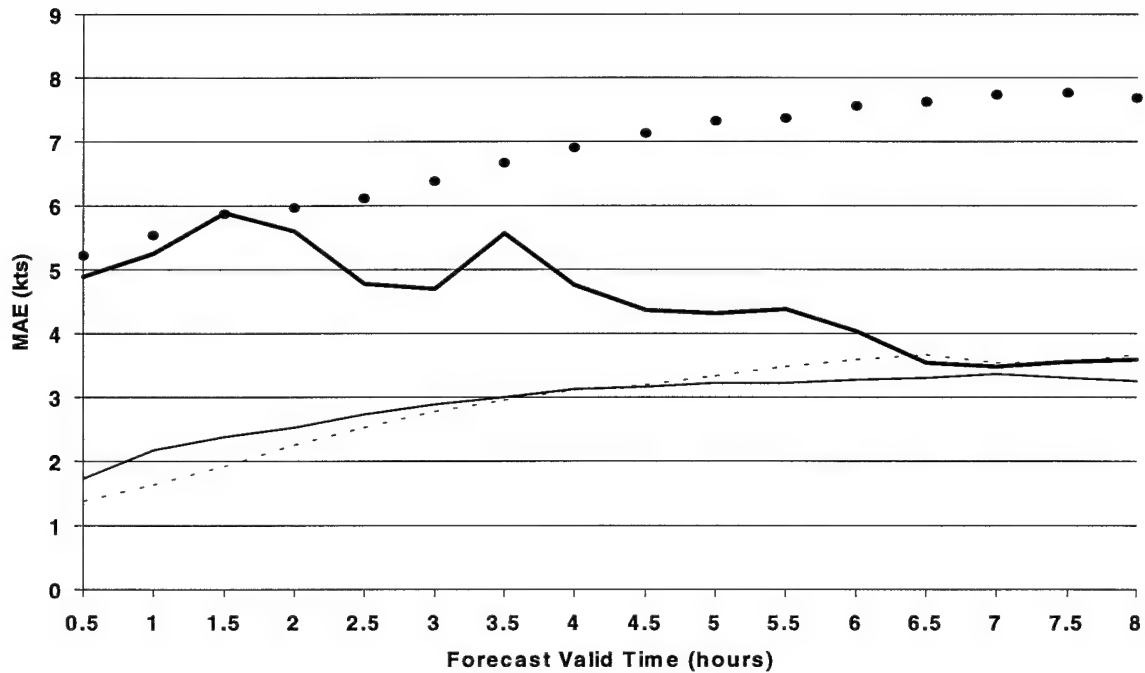


Figure 5.1. Mean Absolute Error (MAE) vs. Forecast Valid Time for Data Subset 3. Graph shows average MAEs for all data periods in Subset 3 for forecasts using the Original Method neural nets (dotted line), the Variation Method neural net (thick solid line), Variation Method persistence (thin solid line), and Original Method persistence (dashed line).

approach may not add much value to the process of predicting for valid times early in the forecast period. Using a neural network to complement the methods in use for predicting winds late in the forecast period, however, could reduce errors in predicting peak winds for those forecast valid times.

5.3 Reliability Intervals

Displays of the reliability intervals described in Chapter 4 are presented in Figures 5.18 through 5.20. Each figure shows eight notional neural net 8-hour forecasts for random forecast start times in the indicated data period. Additional plots are presented in Appendix E.

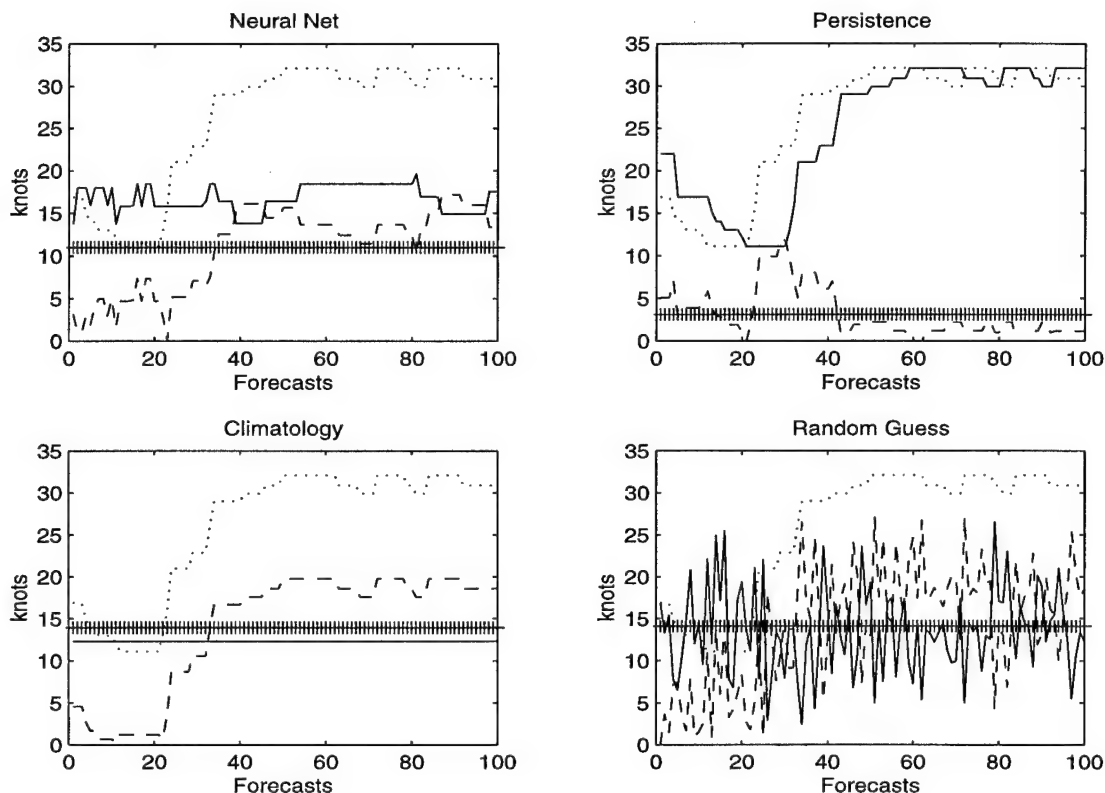


Figure 5.2. Half-hour Forecasts from 24 January – 1 February 1996 Using the Variation Method. Forecasts are plotted as solid lines, verifications as dotted lines. Mean absolute errors (MAEs) between forecasts and verifications are plotted as dashed lines, and the average MAE for all 100 forecasts is plotted as a series of +'s.

The neural net forecast plots (dotted lines) in Figures 5.18 through 5.20 appear reasonable and closely track the verification plots (solid lines). Other forecasts, however, are wildly erratic and do not come close to the observed peak wind (see Appendix E).

It was hoped that the reliability intervals would bound the majority of the verification plots, but this was not the case. A possible weakness in the method applied here may have been using too few samples to determine the statistics for the mean absolute errors in a particular network's forecasts. Perhaps several thousand samples of MAE should be analyzed, instead of only 100.

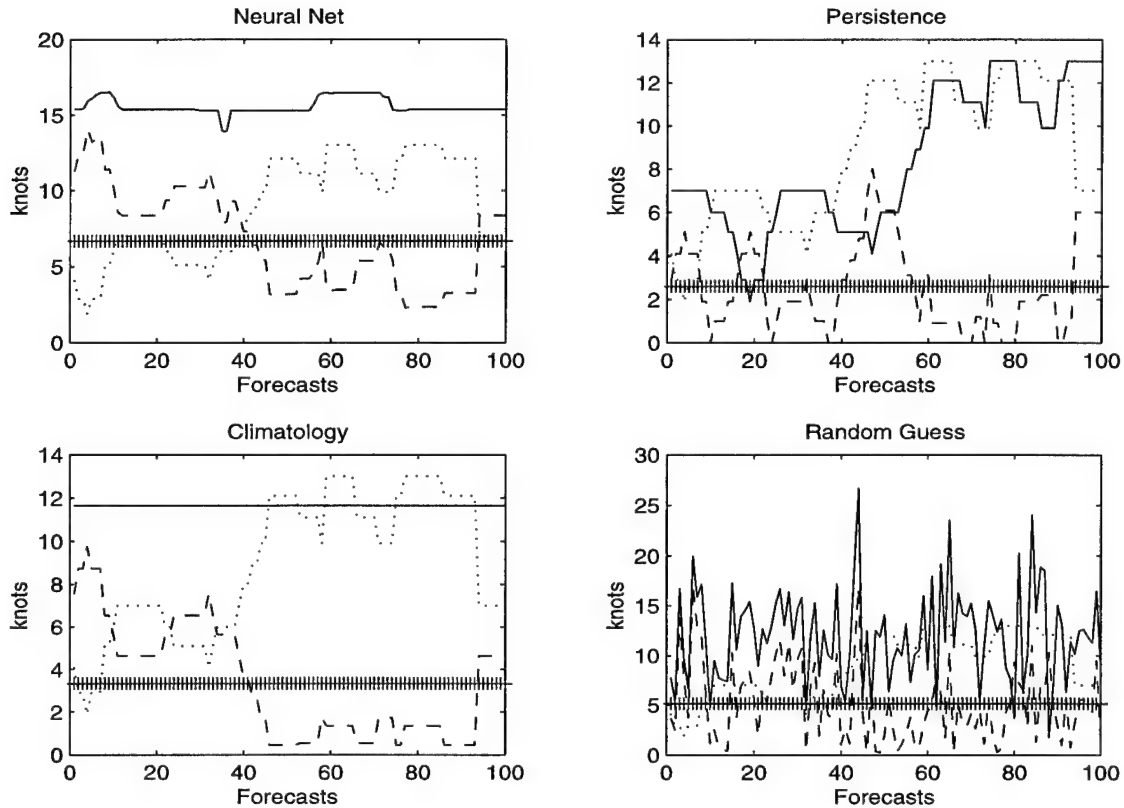


Figure 5.3. As in Fig. 5.2, but for 1-hour Forecasts during 5-13 December 1995.

5.4 Operational Use

The results of this research suggest the following operational use of a neural network: Nine hours before launch, train the neural net on data from the previous $3\frac{1}{2}$ days, up to the current time. (During this research training a 10-neuron, 3-delay network on 1,000 data points [approximately $3\frac{1}{2}$ days] took about 45 minutes.) A few minutes before the pre-launch 8-hour window, use the trained network to generate a forecast with the most recent data available. (The neural net requires only a few seconds to generate its 8-hour forecast.) Based on this study, wind forecasts for valid times later in the period will probably be the most accurate.

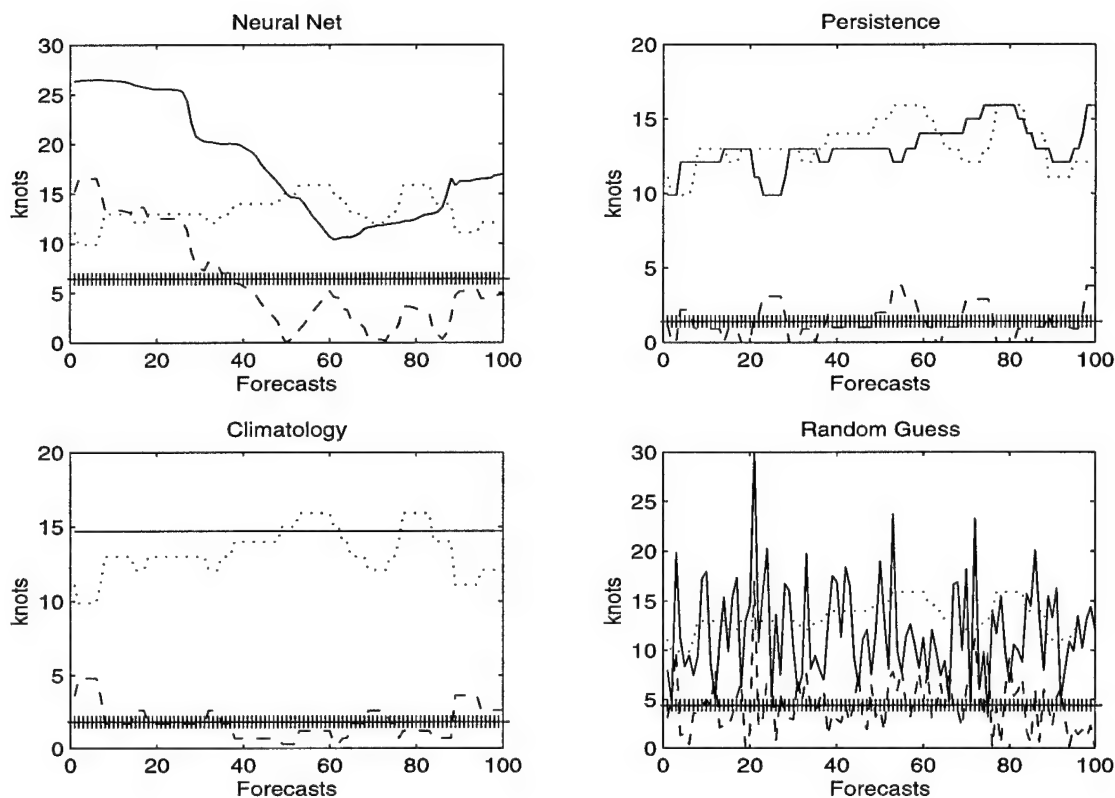


Figure 5.4. As in Fig. 5.2, but for 1.5-hour Forecasts during 14-22 December 1996.

5.5 Further Study

Limiting the neural network inputs to those elements recorded by the WINDS tower undoubtedly eliminated several potential predictor variables. Using the MATLAB code developed in this study, a researcher can incorporate additional data from other sources to potentially improve the network's forecast skill. Primary candidates for additional inputs would be measures of the local temperature and pressure gradients. The vertical temperature gradient and vertical wind shear would be particularly important and could be used as separate inputs or used to compute the Richardson number, which could be used as an input.

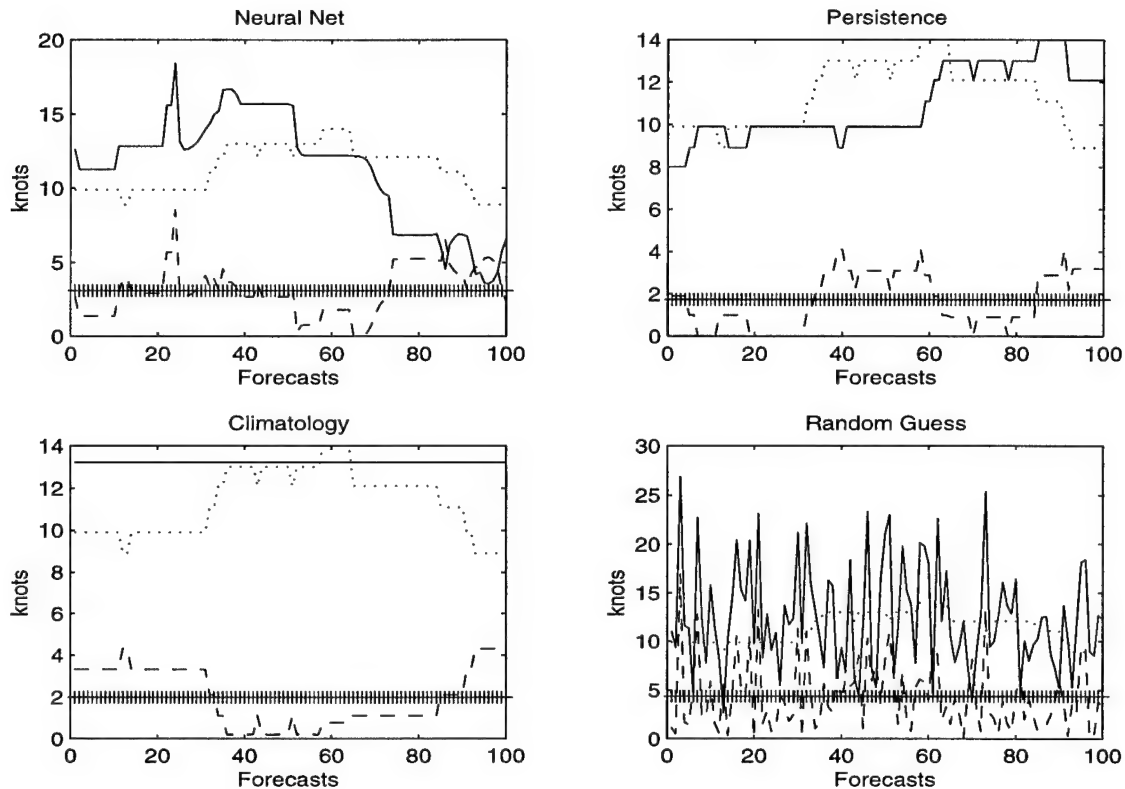


Figure 5.5. As in Fig. 5.2, but for 2-hour Forecasts during 23 February – 7 March 1996.

Pre-processing the input data candidates (using principle components analysis, for example) would provide insight into any redundancies in the inputs and indicate which inputs should be eliminated in order to avoid high correlations between input data pairs. Correlations between inputs can confuse the network into assigning high importance to a variable that is not really a valid predictor of the target element. For example, if inputs A and B are highly correlated and A is a good predictor of the target output, B will appear to be a good predictor too, and B's weights will be adjusted accordingly (but erroneously). B, a bogus predictor, would have undue influence on the network outputs, and other more valid predictors may not be permitted to contribute to the solution.

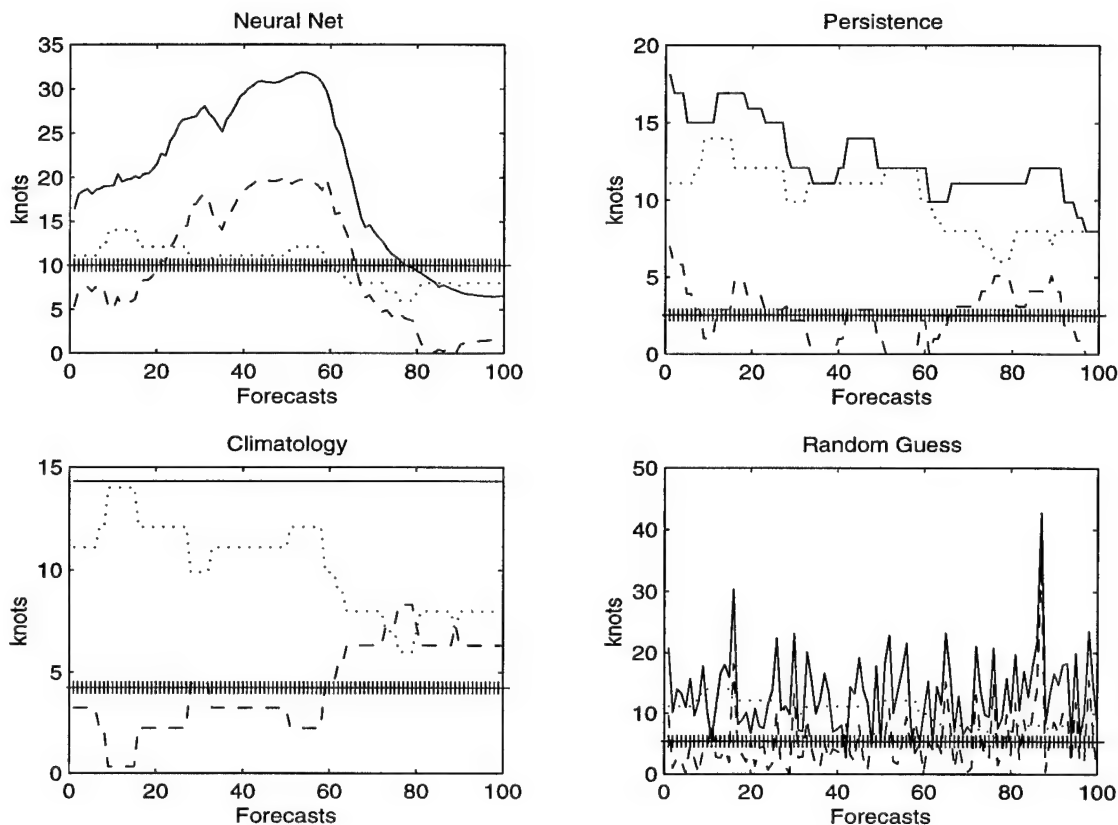


Figure 5.6. As in Fig. 5.2, but for 2.5-hour Forecasts during 6-21 January 1997.

Other forms of data analysis may provide insight into the best training and architecture to use. In particular, an in-depth Fourier analysis of the peak wind signal may uncover a clue to the appropriate number of delays to use. If, for example, the power function of frequency indicated a strong signal at 30 minutes, half-hour moving averages of the peak wind may represent a better input than one-hour averages.

A climatological stratification of various conditions may give insight into which inputs would serve as good predictors. Assuming different atmospheric mechanisms vie for control of the peak wind speed throughout the day, separate neural networks for different parts of the day could be developed. This approach could be extended to

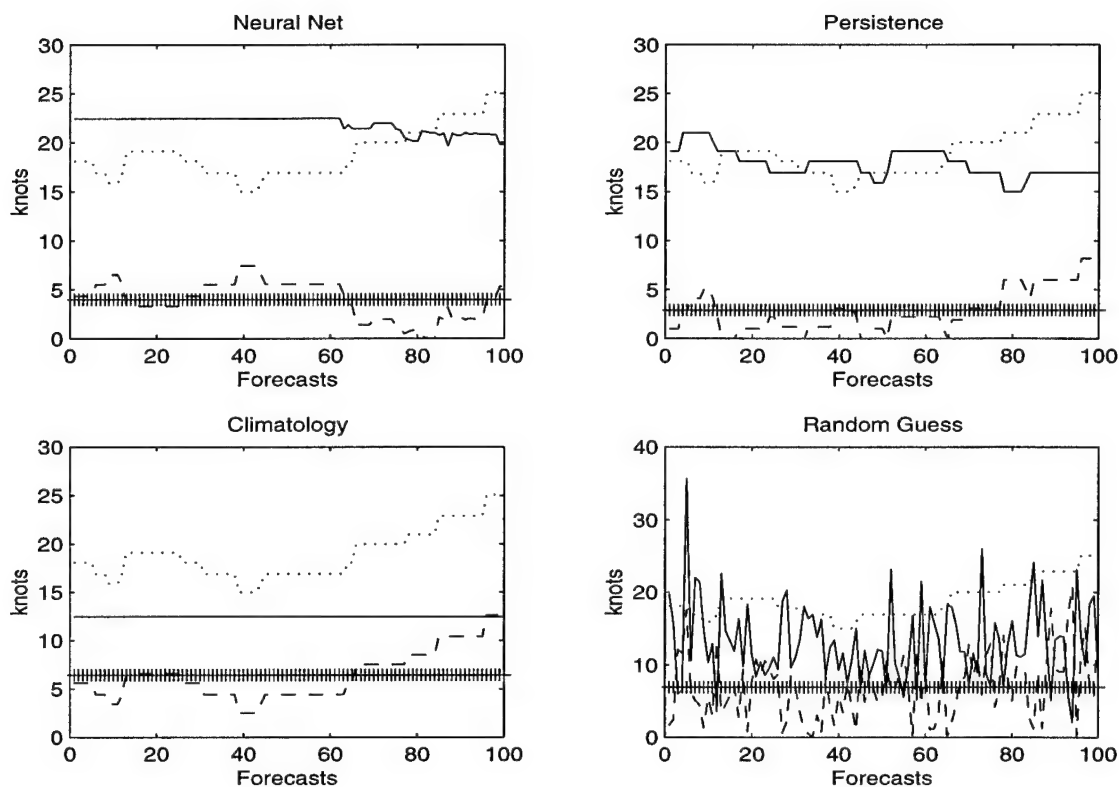


Figure 5.7. As in Fig. 5.2, but for 3-hour Forecasts during 24 November – 8 December 1996.

include stratifications based on synoptic regimes in place at certain times of the season.

A suite of neural network architectures could be developed and kept on hand for immediate training when LWOs recognized a particular regime setting up.

On the other hand, a form of ensemble forecasting may prove beneficial, regardless of which regime is in place at a particular time. Several forecast runs using different network architectures could be generated. The ensemble forecast average could be used as the final forecast. Alternatively, a given network architecture could be trained on the same set of inputs and targets several times, with weights and biases initialized to

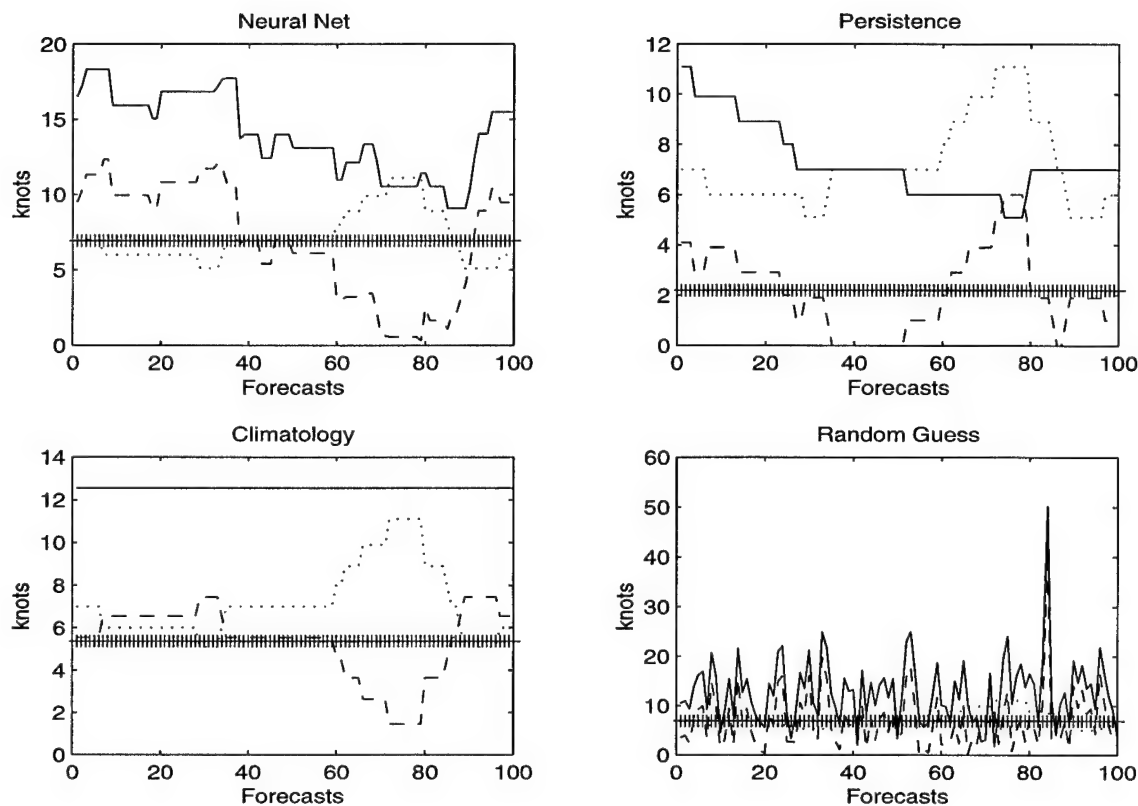


Figure 5.8. As in Fig. 5.2, but for 3.5-hour Forecasts during 25 November - 2 December 1997.

random values each time. This approach would permit several network attempts at finding the optimum weight and bias values.

Theoretically, training only on specific types of wind events would produce a network capable of predicting similar events well. Although one of the strengths of neural networks is their ability to generalize, this feature is not limitless, and a neural net is only as good as its inputs. Instead of a one-size-fits-all approach like the one originally employed in this research, a suite of four or five networks, with each network tailored to forecast during a particular atmospheric regime, may provide the right balance between

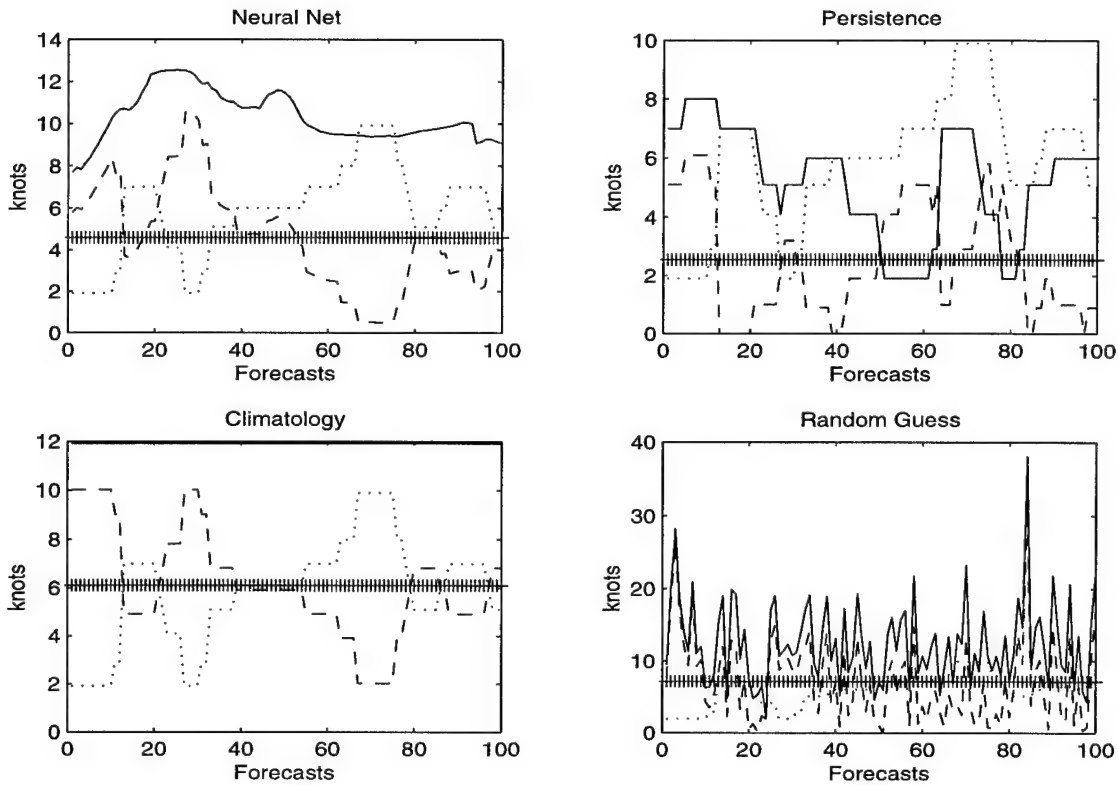


Figure 5.9. As in Fig. 5.2, but for 4-hour Forecasts during 29 January – 6 February 1997.

robustness and accuracy. The improvements seen in using the variation of the original method used in this study confirm the need to carefully choose training criteria.

The nuts and bolts of neural network development could also be adjusted. For instance, training a network with an architecture similar to the one used in this research for several hundred epochs instead of only 20 may allow the network to settle on a better set of weights and biases than those found here. Experimenting with different numbers of delays and hidden layer neurons may also uncover an architecture that generates more accurate forecasts. The MATLAB code developed in this study makes adjusting the numbers of delays and neurons easy.

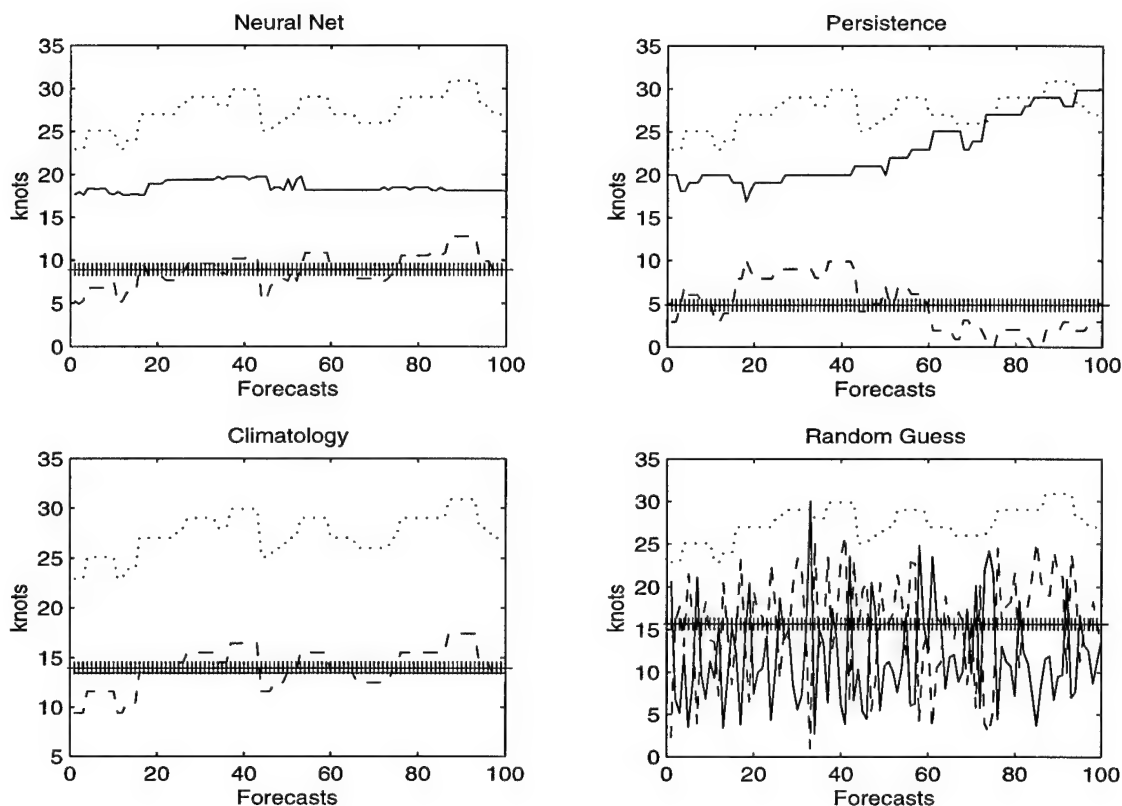


Figure 5.10. As in Fig. 5.2, but for 4.5-hour Forecasts during 4-18 March 1998.

Finally, using a neural network to post-process forecast data generated by other methods may prove beneficial. For example, the LWO's estimate of the peak wind, Model Output Statistics guidance, and climatology could be used as inputs to the network, which would take the best elements of the other forecasts and produce an optimal forecast.

5.6 Conclusion

To summarize the results of this study, neural networks represent a potentially viable forecasting alternative or addition to LWOs' current forecasting process. Despite the inconclusive results of the original neural network method and the reliability

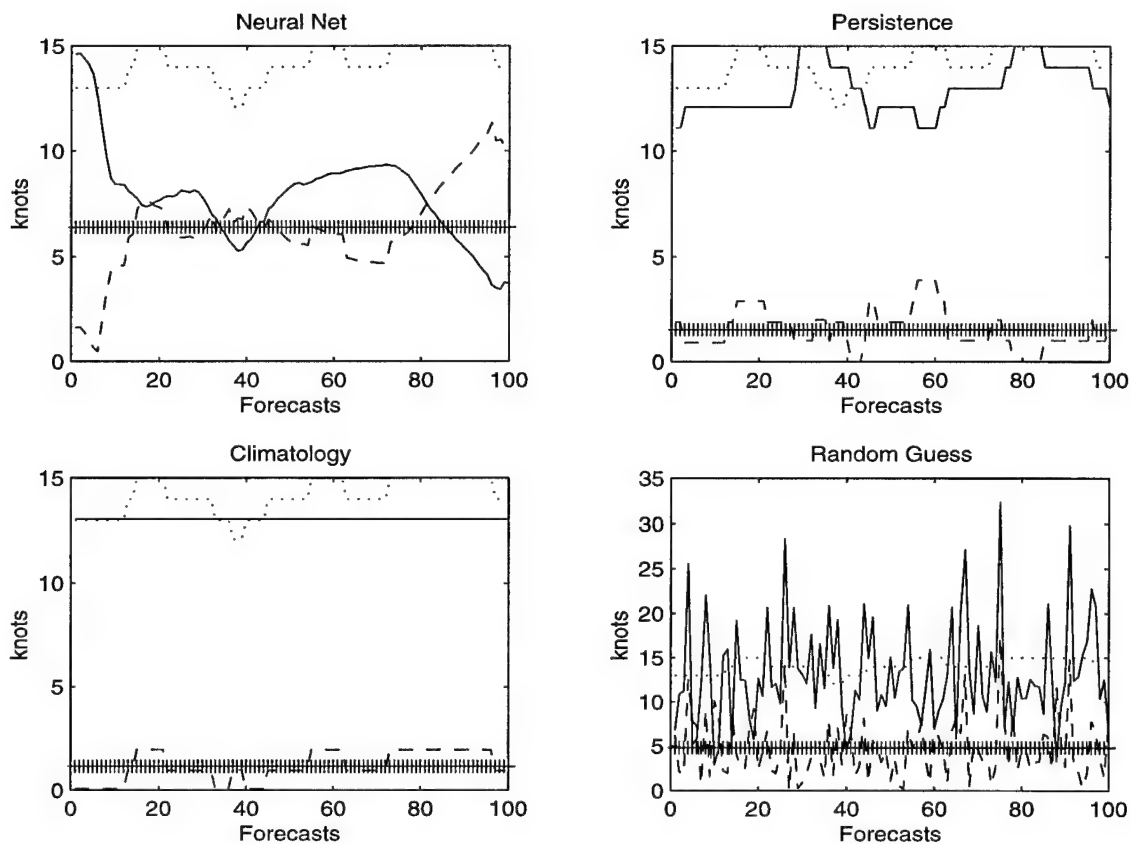


Figure 5.11. As in Fig. 5.2, but for 5-hour Forecasts during 1-10 March 1997.

measure developed in this thesis, the variation on the original method shows promise for wind forecasts late in the 8-hour forecast period.

The variation method showed that greater accuracy was achieved by training a separate network for each data period instead of training one network on thousands of data points spread over several months. Further refinement of the method presented here may result in even better forecasts of wind speed.

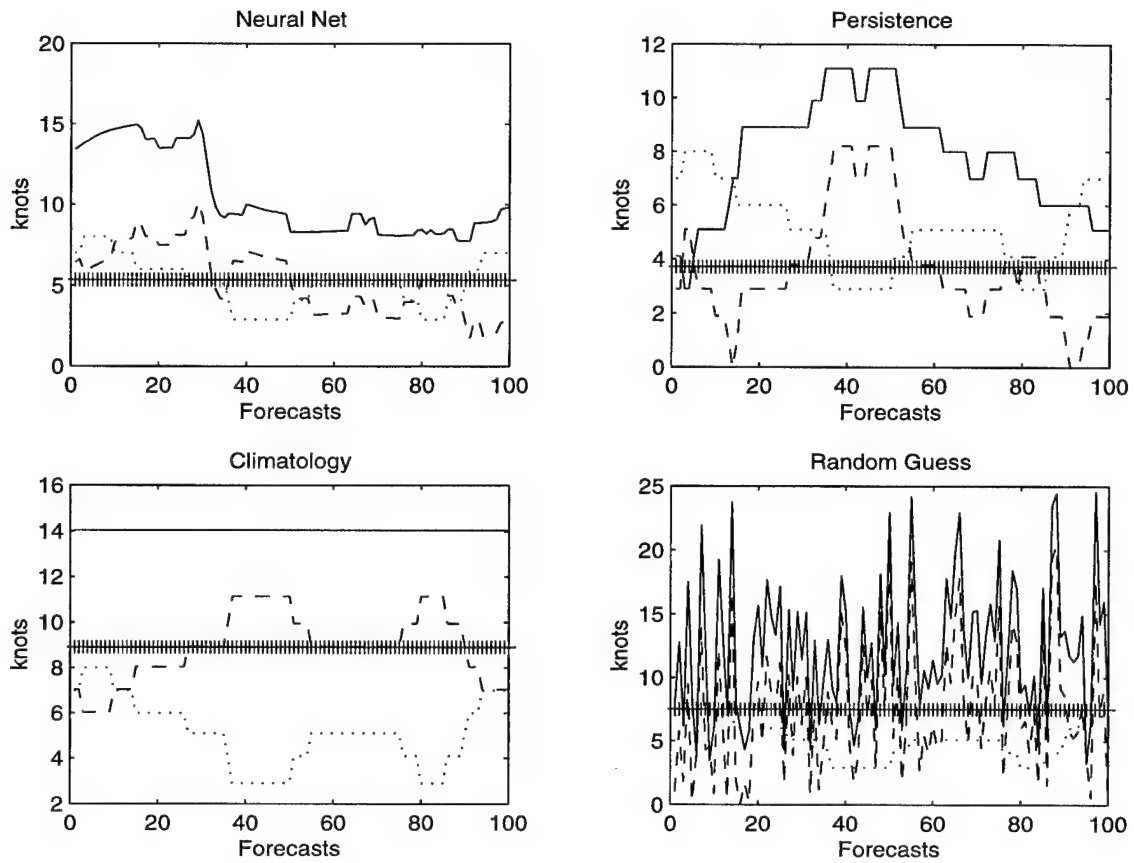


Figure 5.12. As in Fig. 5.2, but for 5.5-hour Forecasts during 8-17 November 1998.

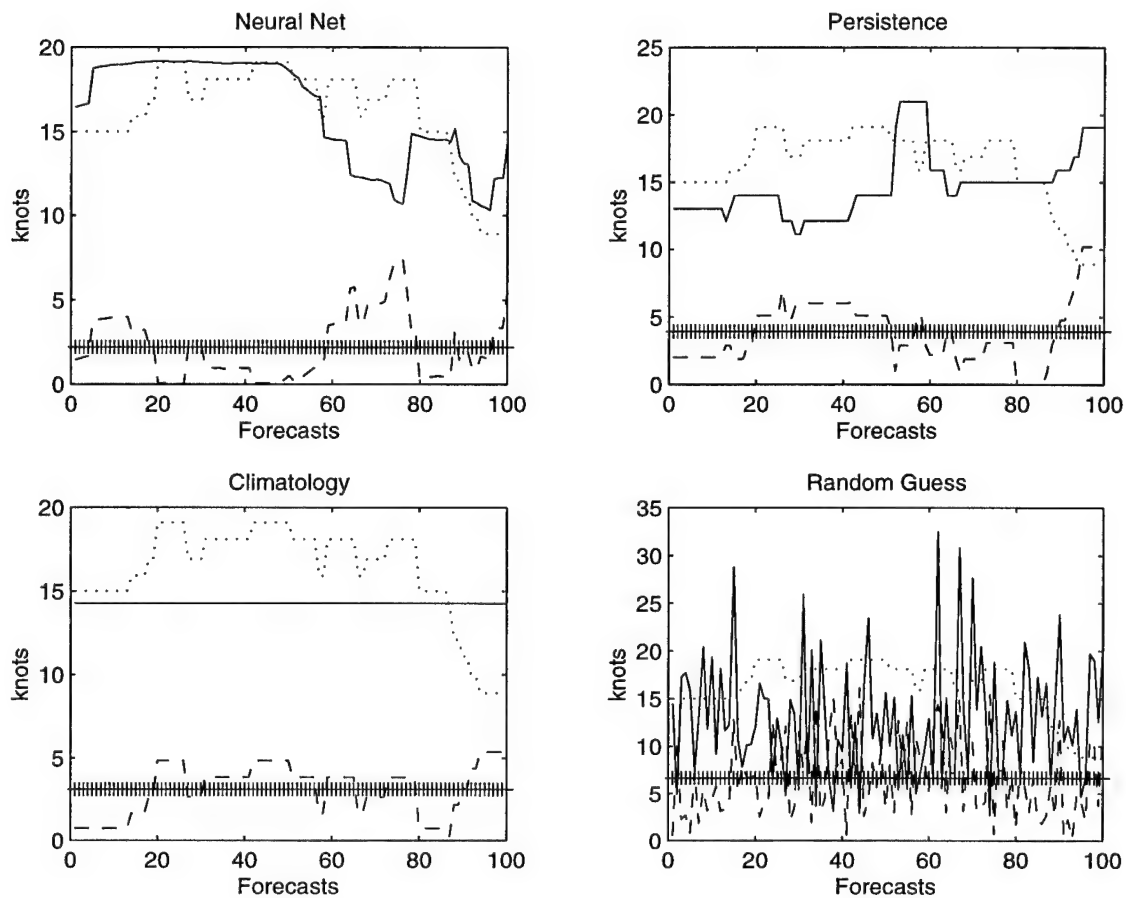


Figure 5.13. As in Fig. 5.2, but for 6-hour Forecasts during 2-13 December 1997.

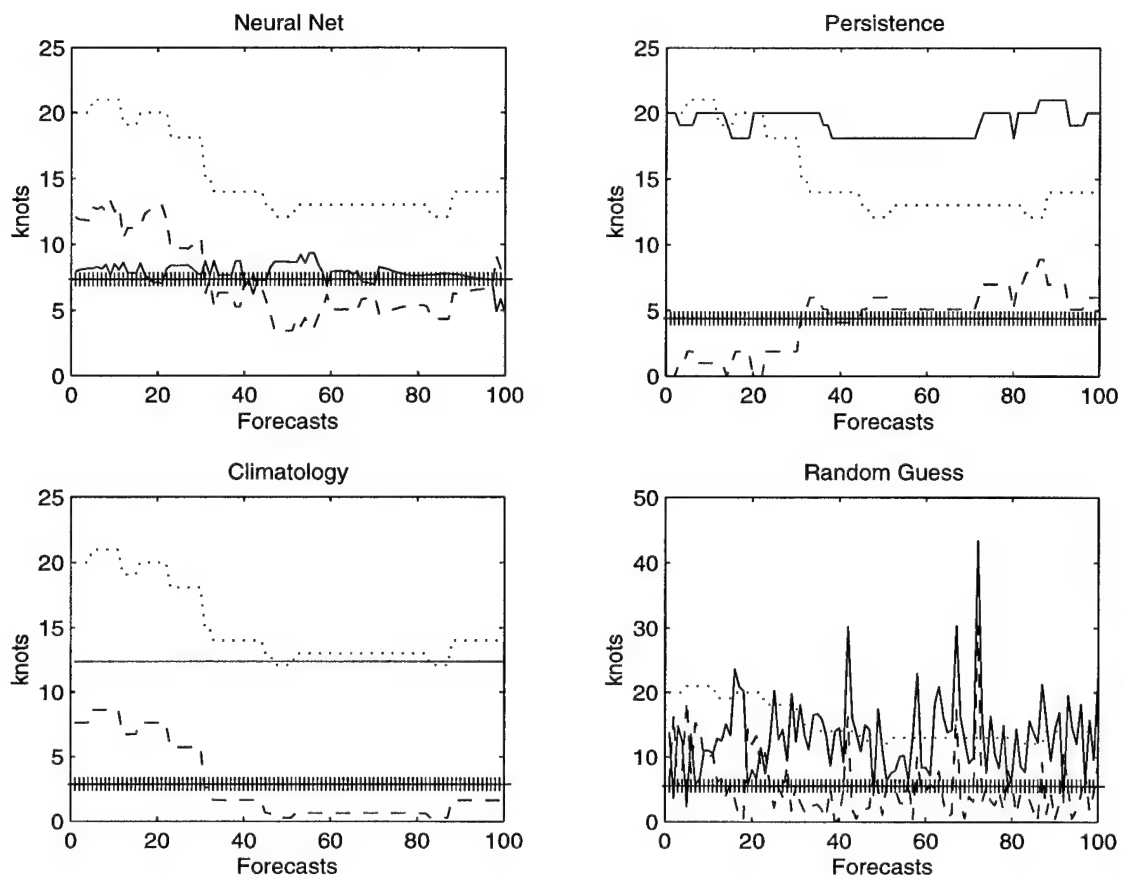


Figure 5.14. As in Fig. 5.2, but for 6.5-hour Forecasts during 14-20 January 1999.

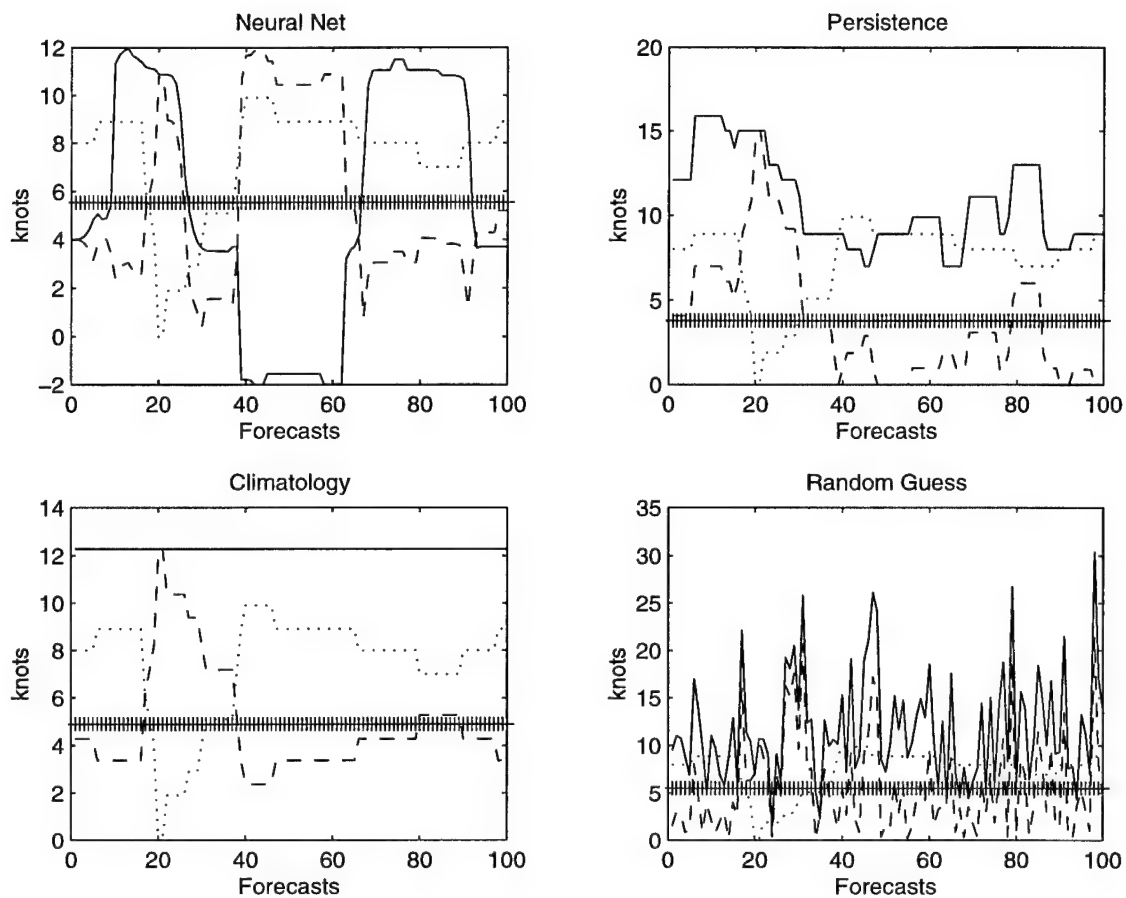


Figure 5.15. As in Fig. 5.2, but for 7-hour Forecasts during 5-11 January 1998.

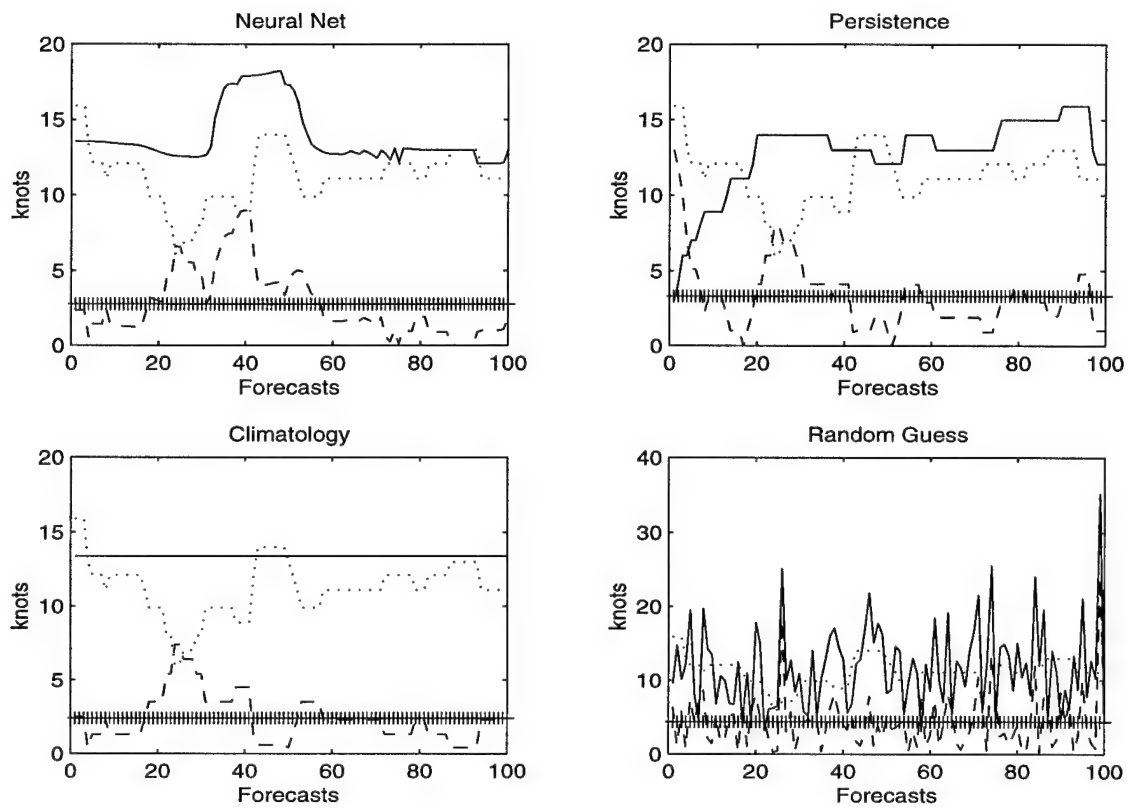


Figure 5.16. As in Fig. 5.2, but for 7.5-hour Forecasts during 21-31 March 1999.

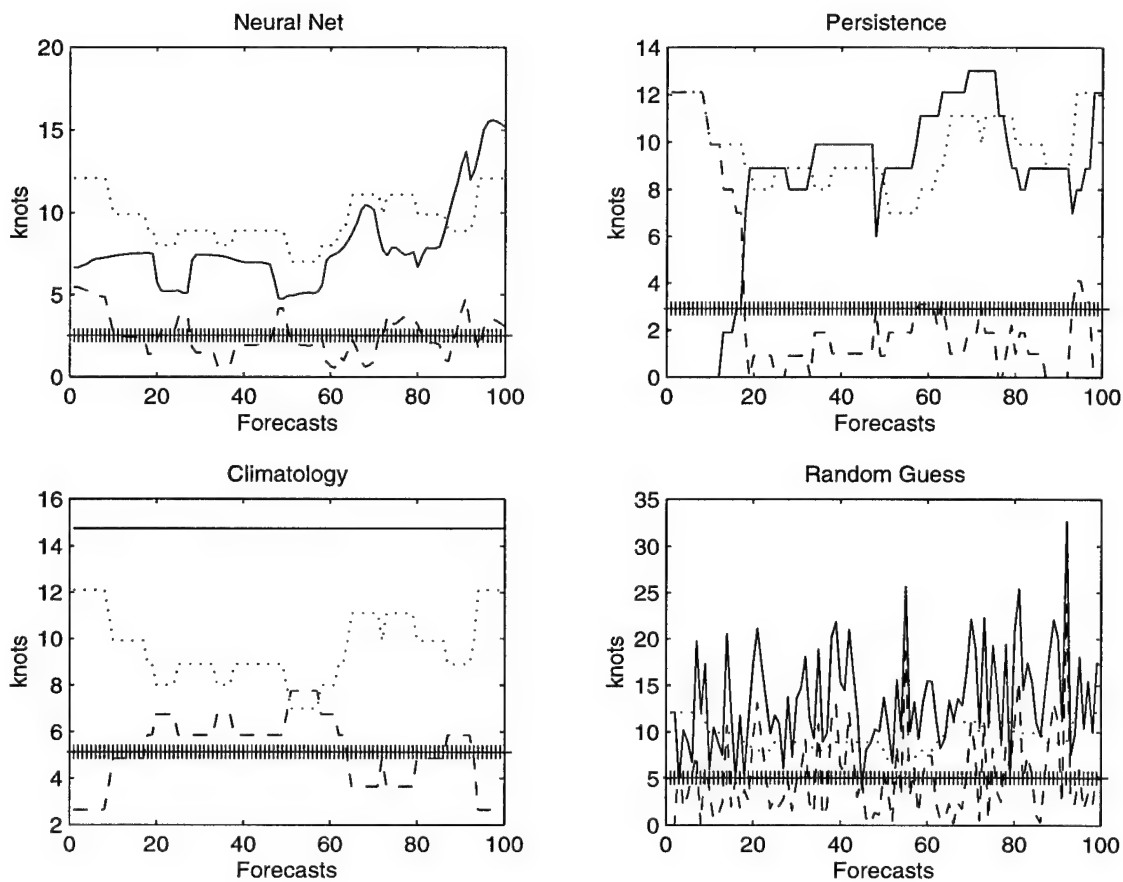


Figure 5.17. As in Fig. 5.2, but for 8-hour Forecasts during 25 January – 4 February 1999.

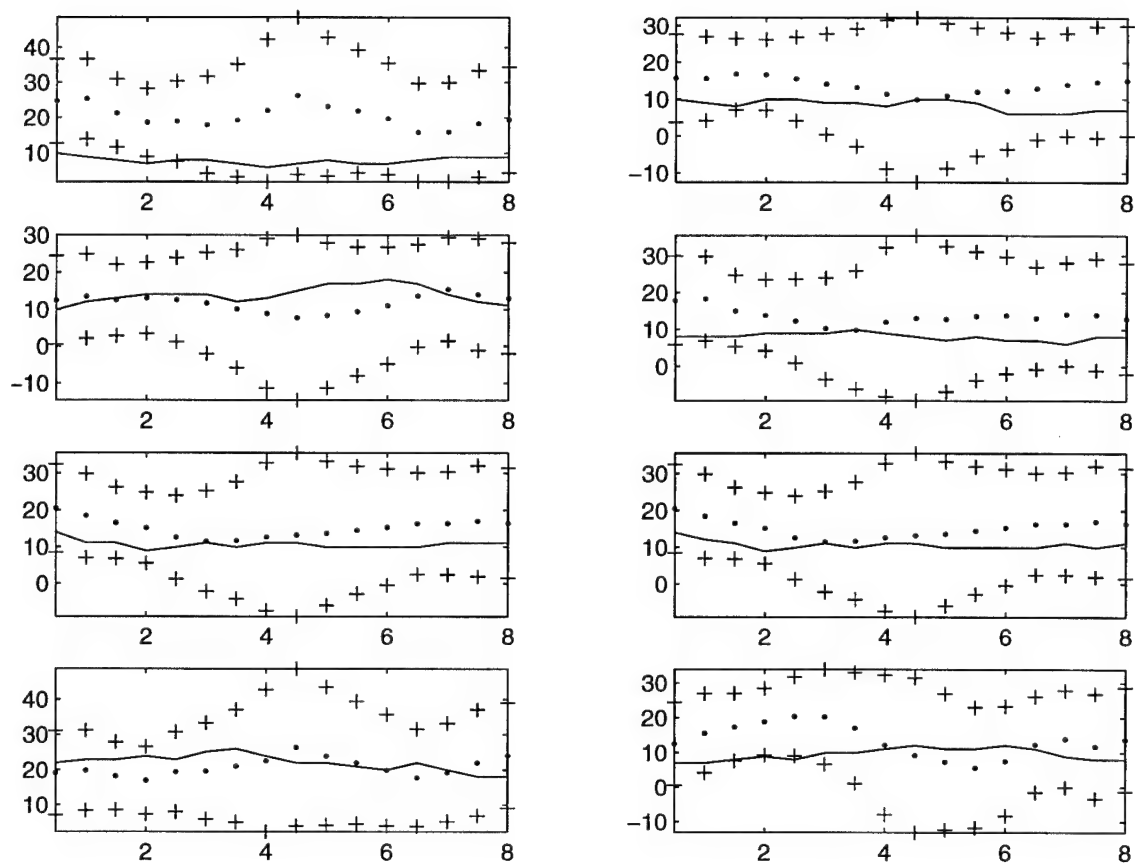


Figure 5.18. Forecasts and Reliability Intervals for 24 January – 1 February 1996. Variation method neural net forecasts are shown as series of dots, and reliability intervals are shown as +’s above and below the forecasts for each valid time. Observed peak wind speeds (solid lines) are shown for comparison. Each of the eight plots represents a different 8-hour forecast with a randomly selected start time.

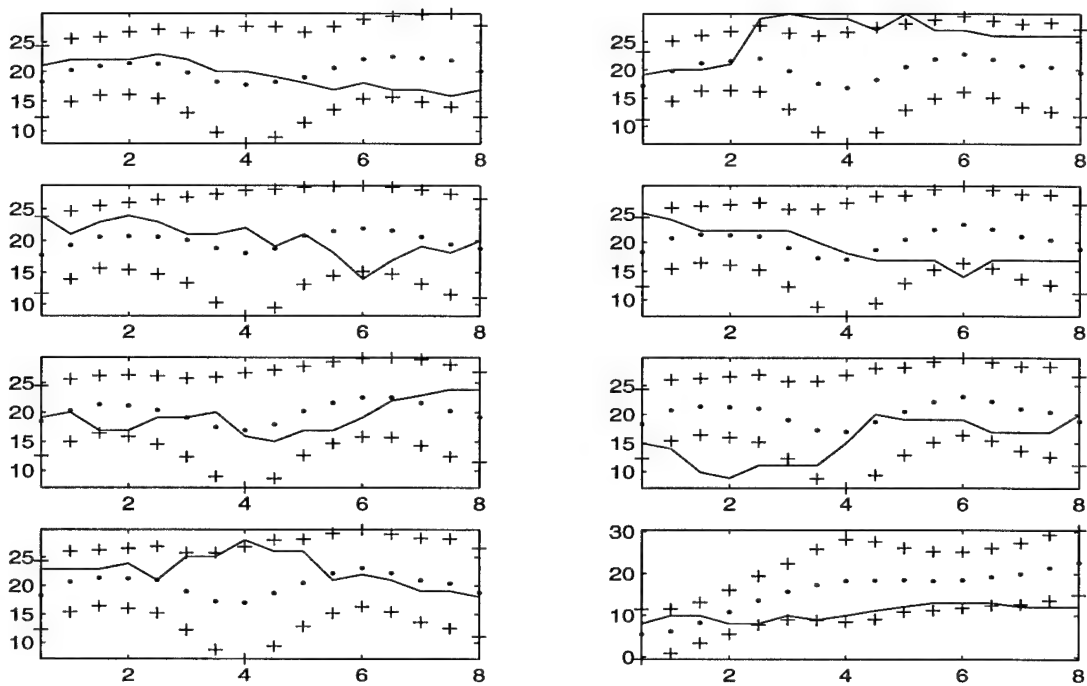


Figure 5.19. As in Fig. 5.18, but for 4-18 March 1998.

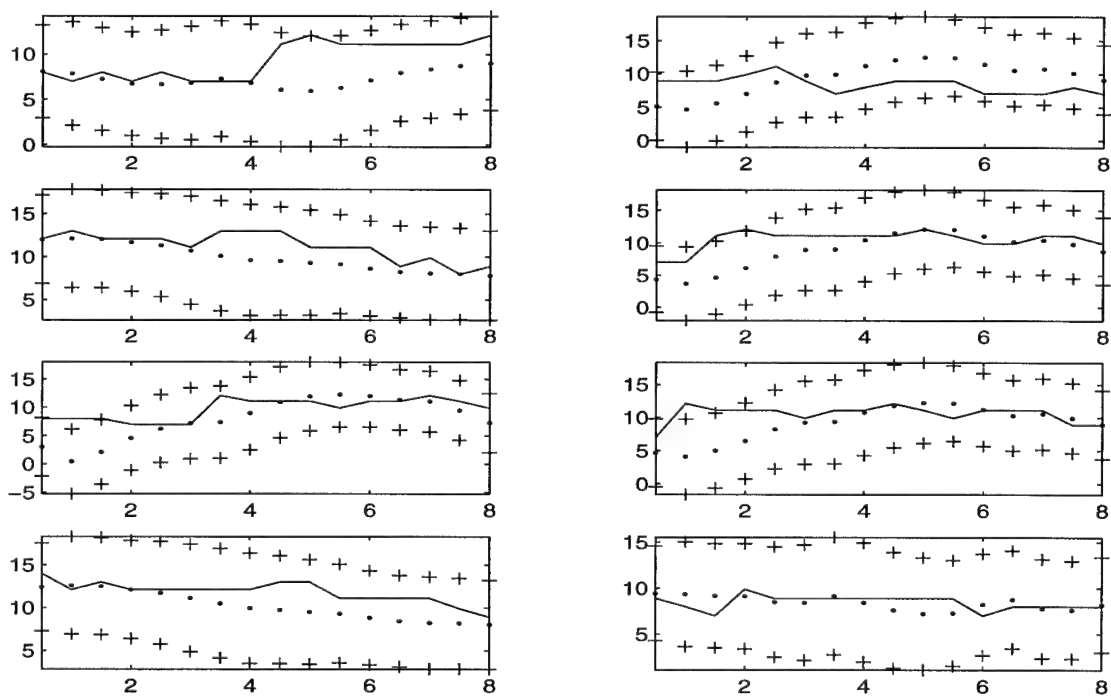


Figure 5.20. As in Fig. 5.18, but for 8-17 November 1998.

Appendix A: Time Series of Peak Wind Speed

This appendix contains plots of 5-minute peak wind speeds for all data periods used in this study. Data were collected at the Atlas Launch Tower 90 feet above the surface.

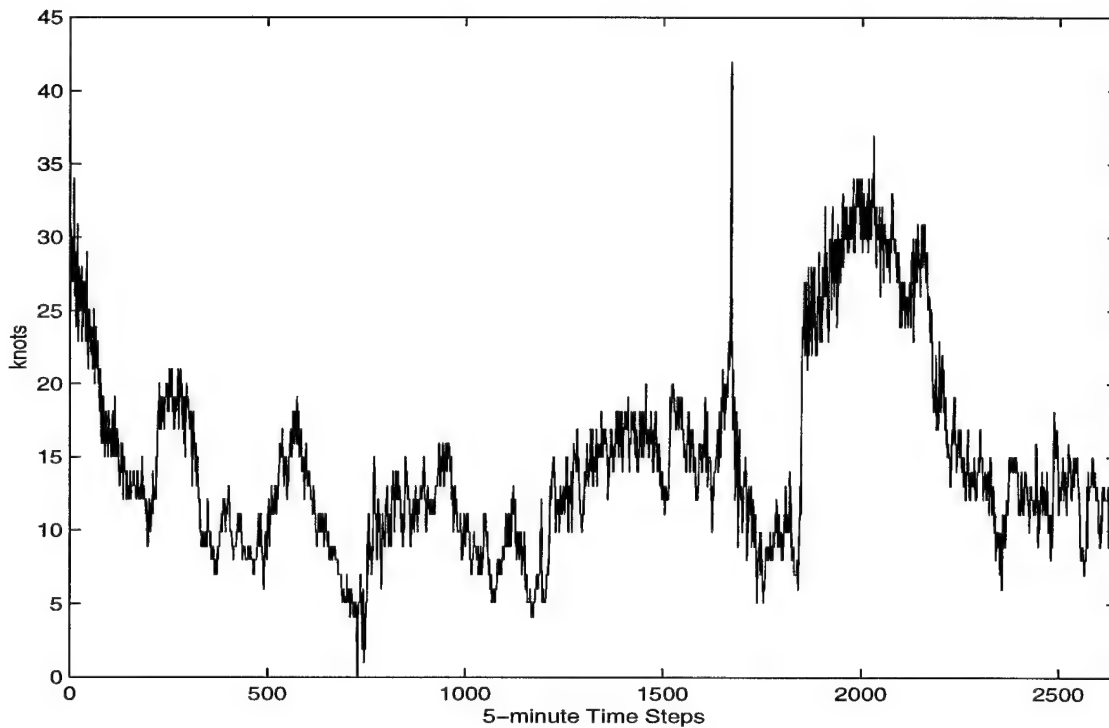


Figure A.1. 5-minute Peak Wind Speed, 2-12 March 1995.

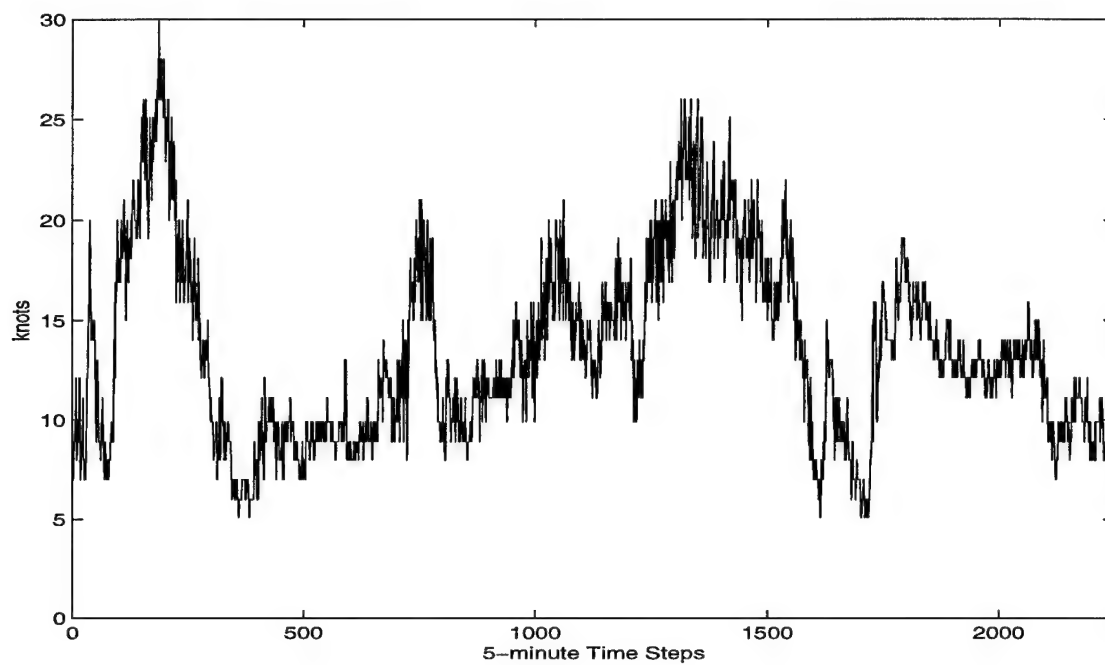


Figure A.2. 5-minute Peak Wind Speed, 19-26 March 1995.

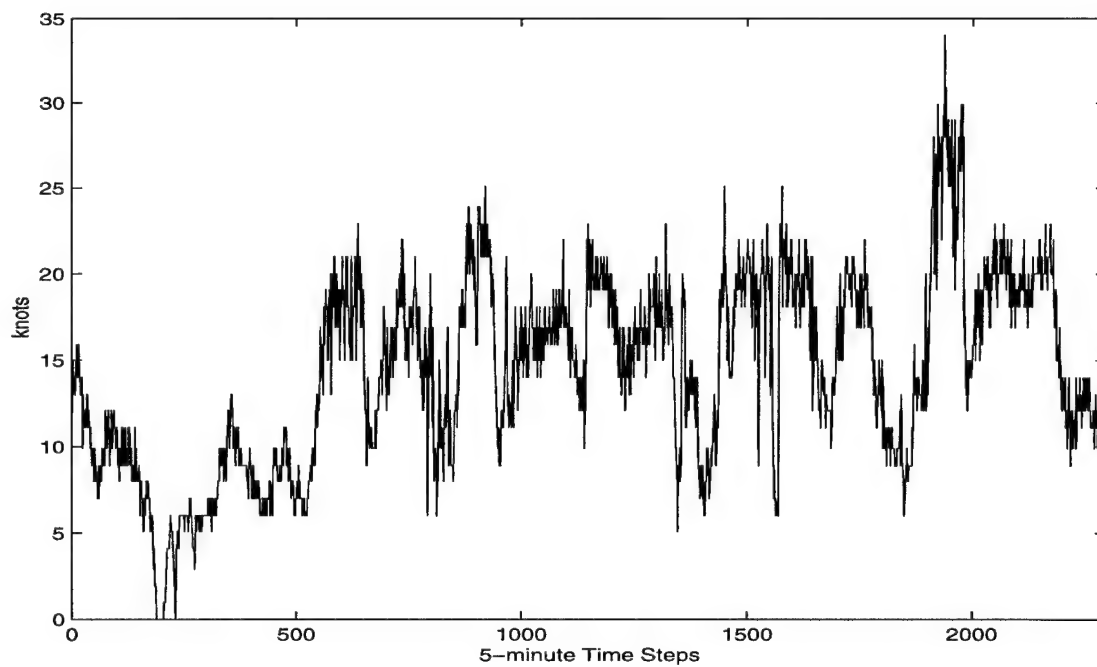


Figure A.3. 5-minute Peak Wind Speed, 4-13 November 1995.

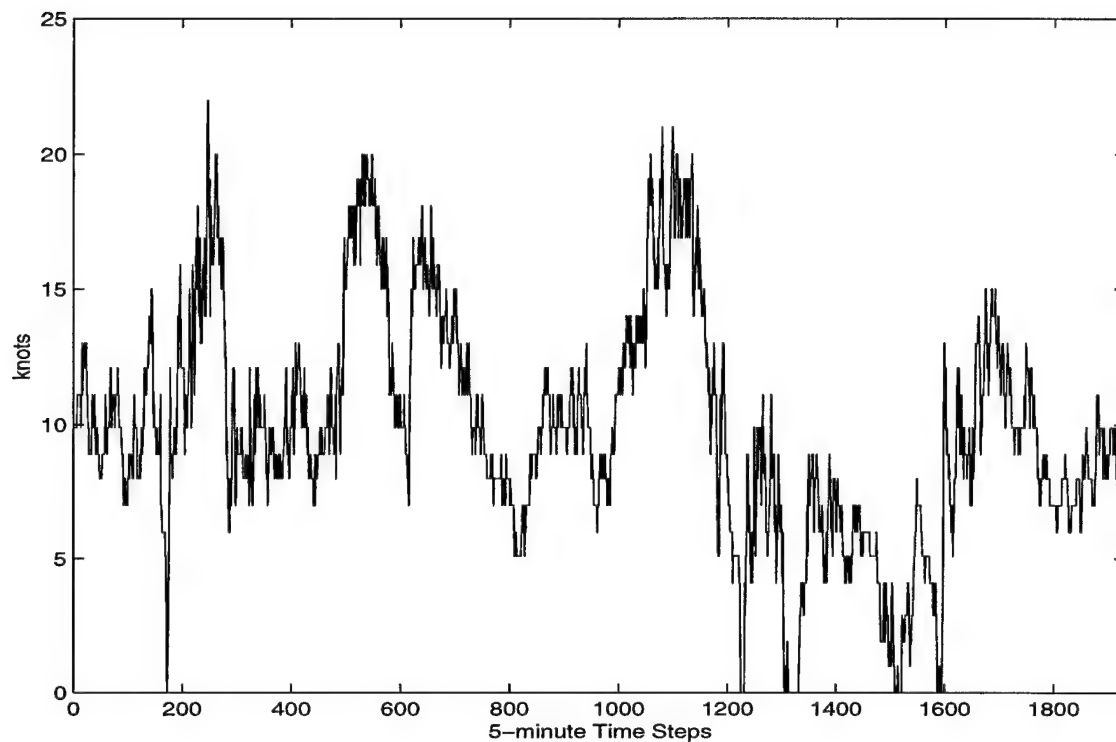


Figure A.4. 5-minute Peak Wind Speed, 28 November – 5 December 1995.

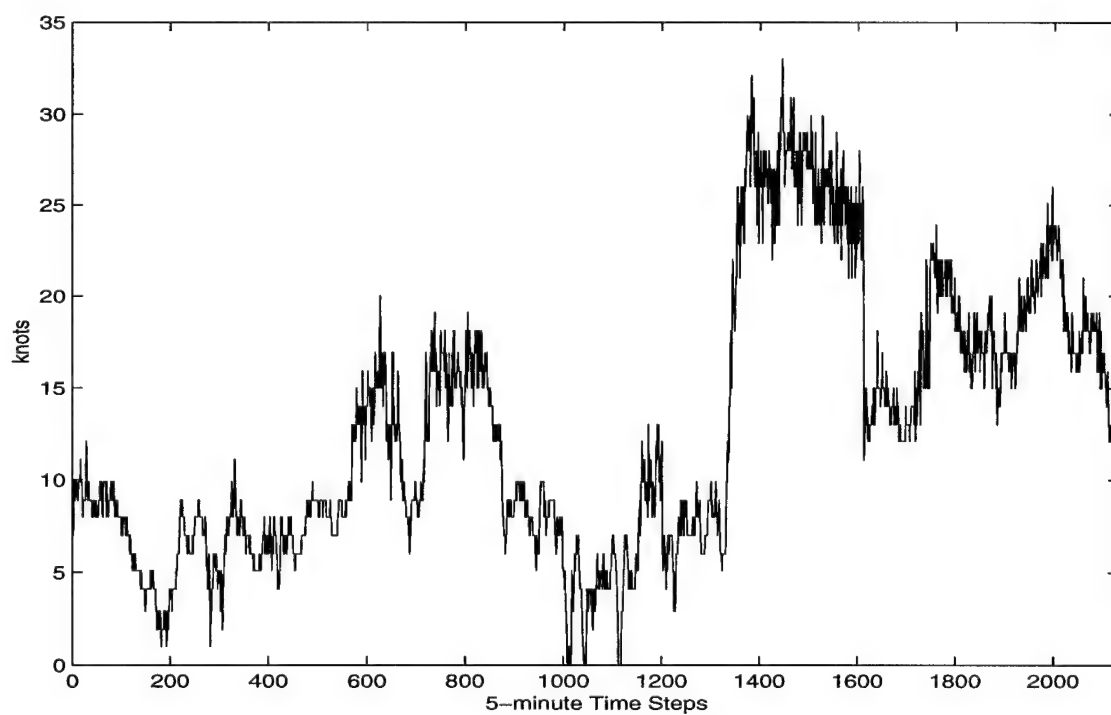


Figure A.5. 5-minute Peak Wind Speed, 5-13 December 1995.

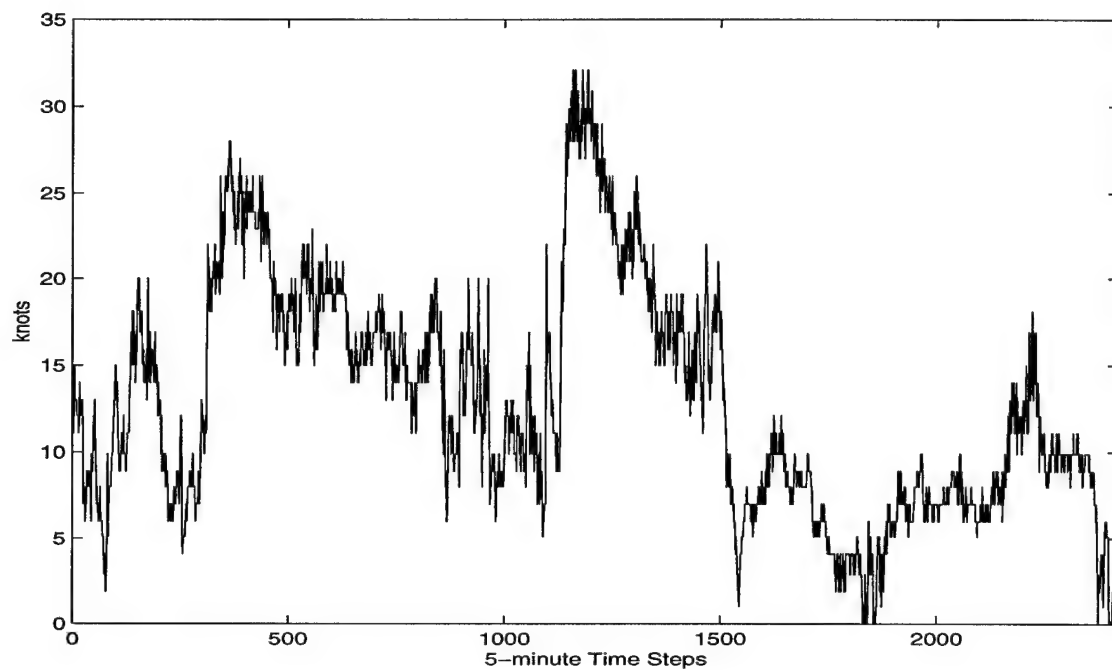


Figure A.6. 5-minute Peak Wind Speed, 24 January – 1 February 1996.

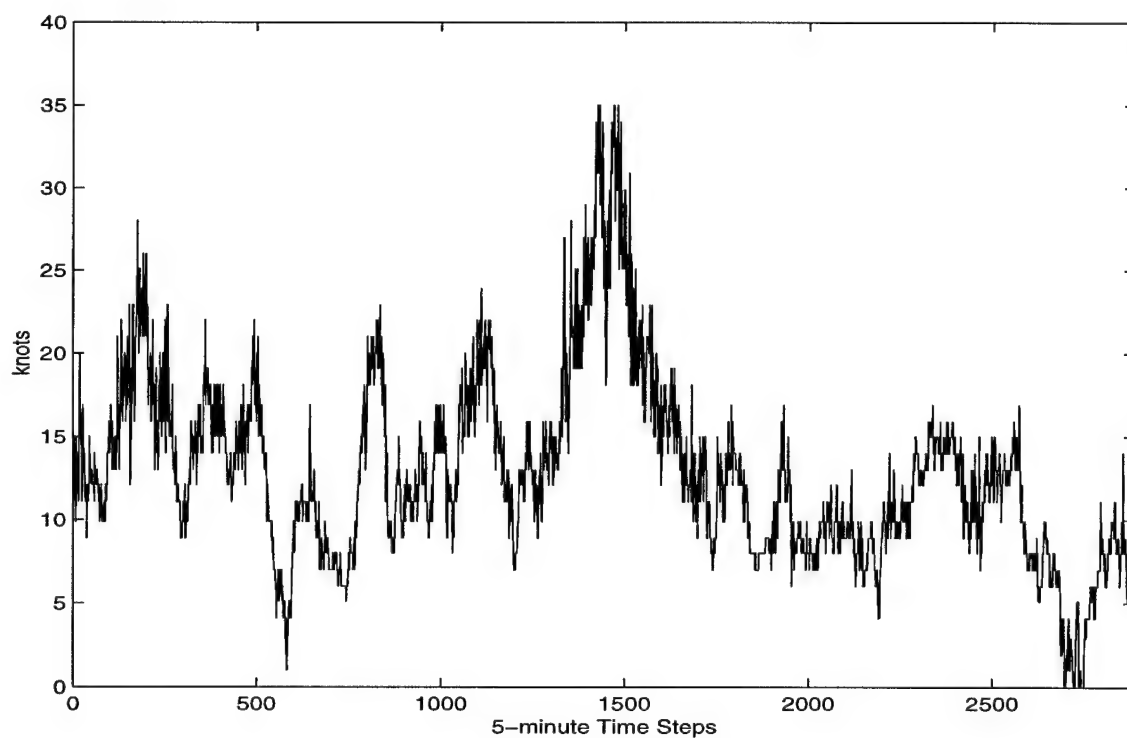


Figure A.7. 5-minute Peak Wind Speed, 11-21 February 1996.

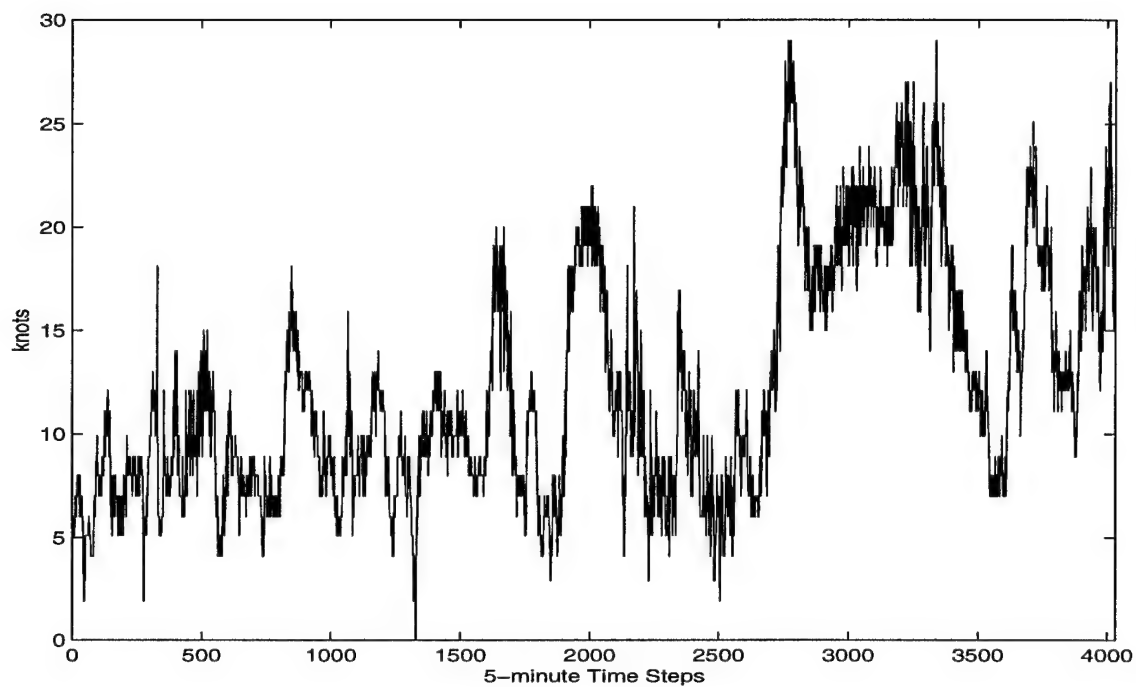


Figure A.8. 5-minute Peak Wind Speed, 23 February - 7 March 1996.

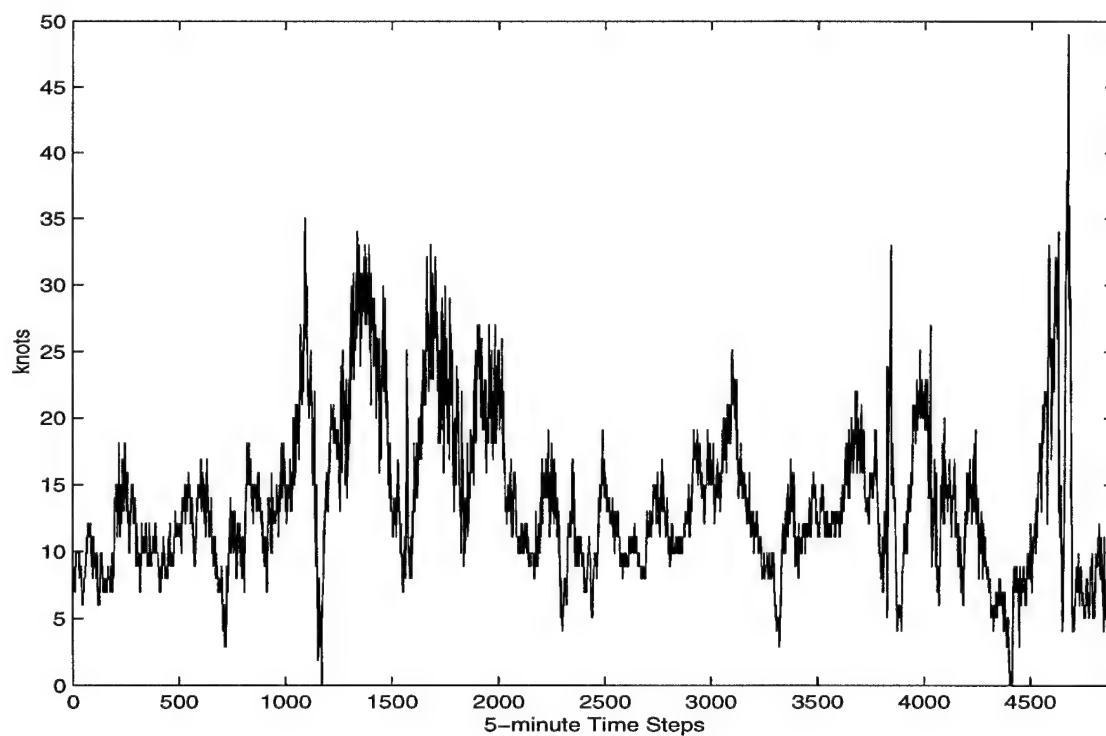


Figure A.9. 5-minute Peak Wind Speed, 15-31 March 1996.

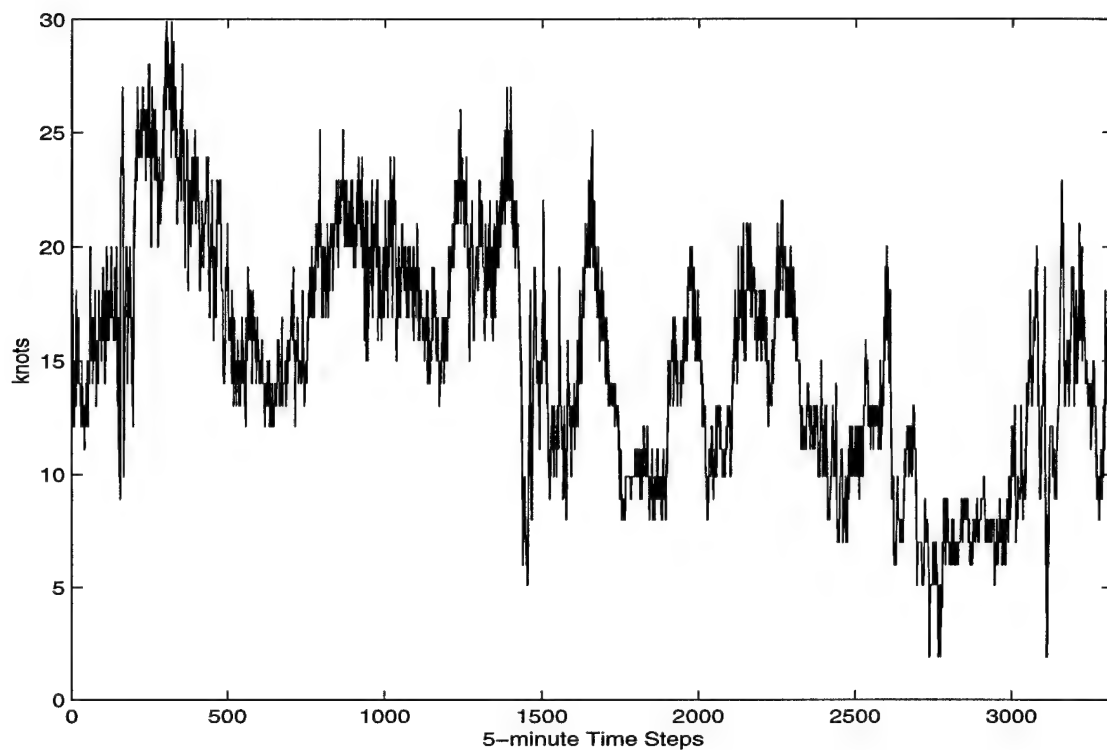


Figure A.10. 5-minute Peak Wind Speed, 24 November – 8 December 1996.

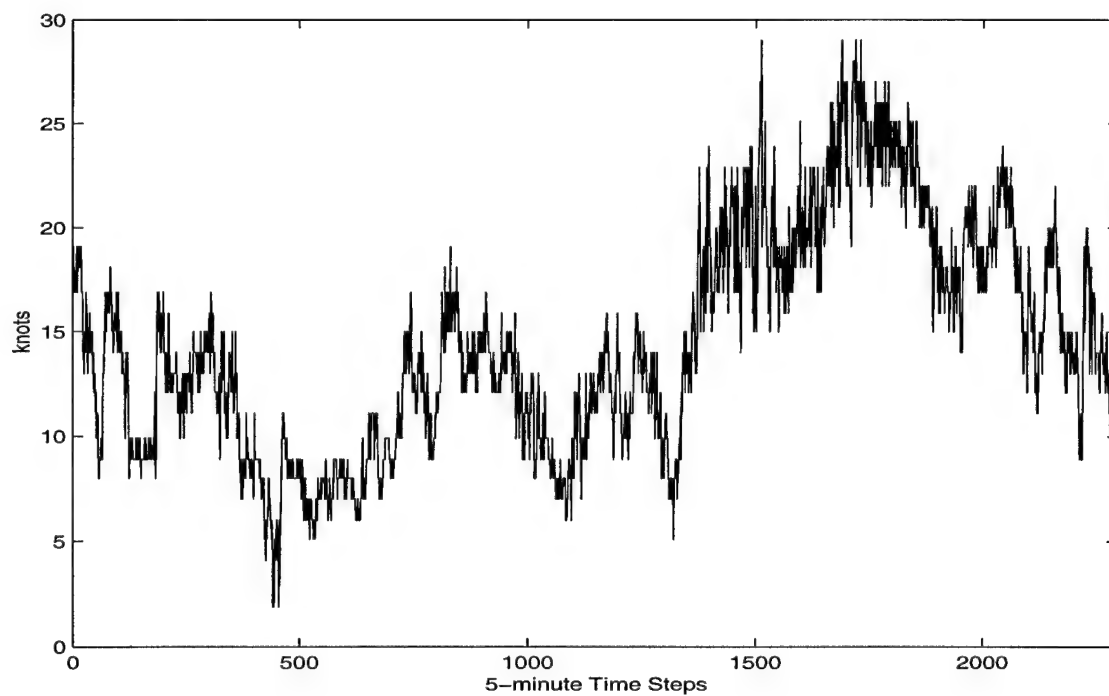


Figure A.11. 5-minute Peak Wind Speed, 14-22 December 1996.

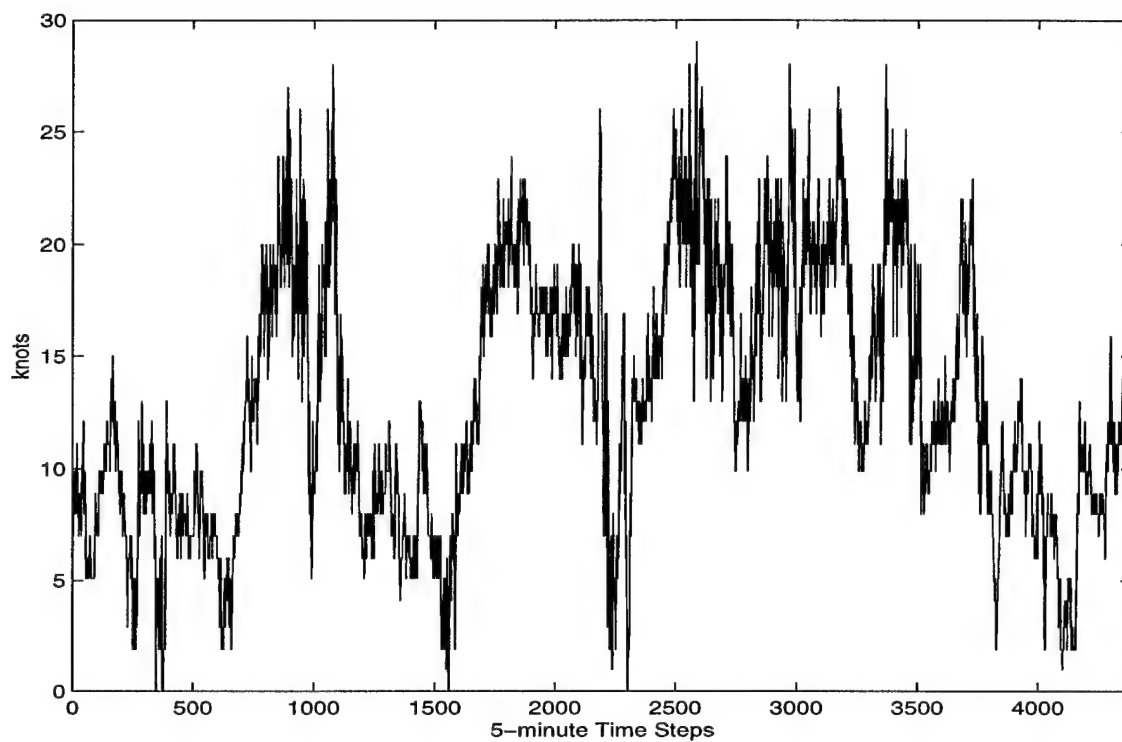


Figure A.12. 5-minute Peak Wind Speed, 6-21 January 1997.

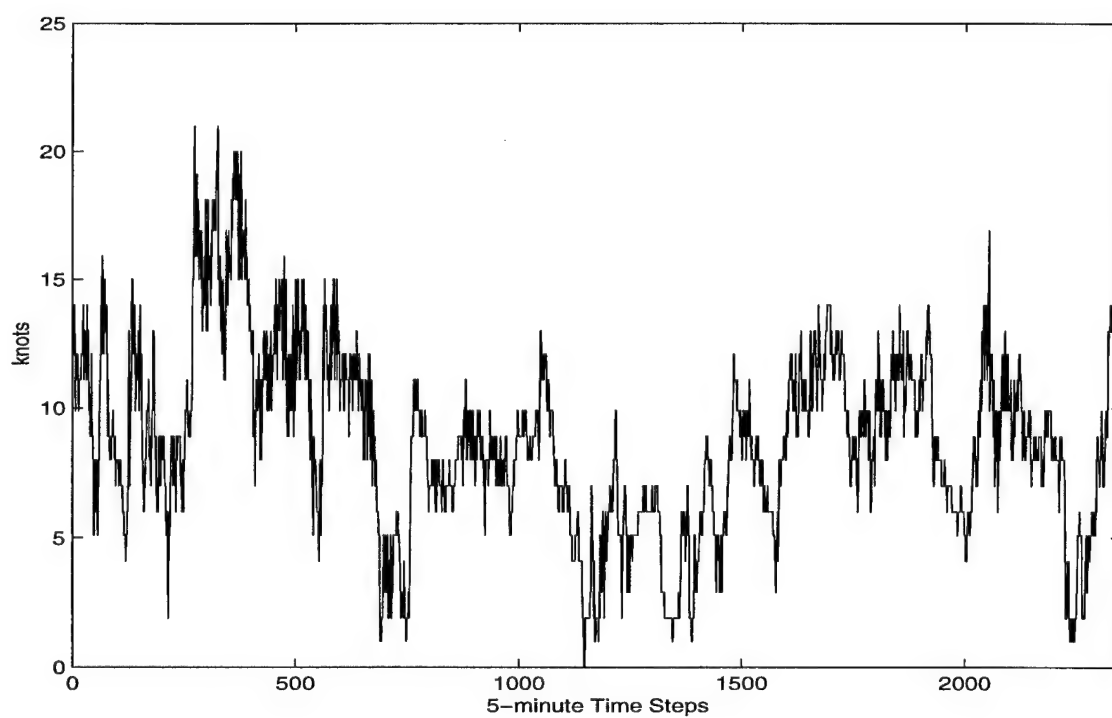


Figure A.13. 5-minute Peak Wind Speed, 29 January – 6 February 1997.

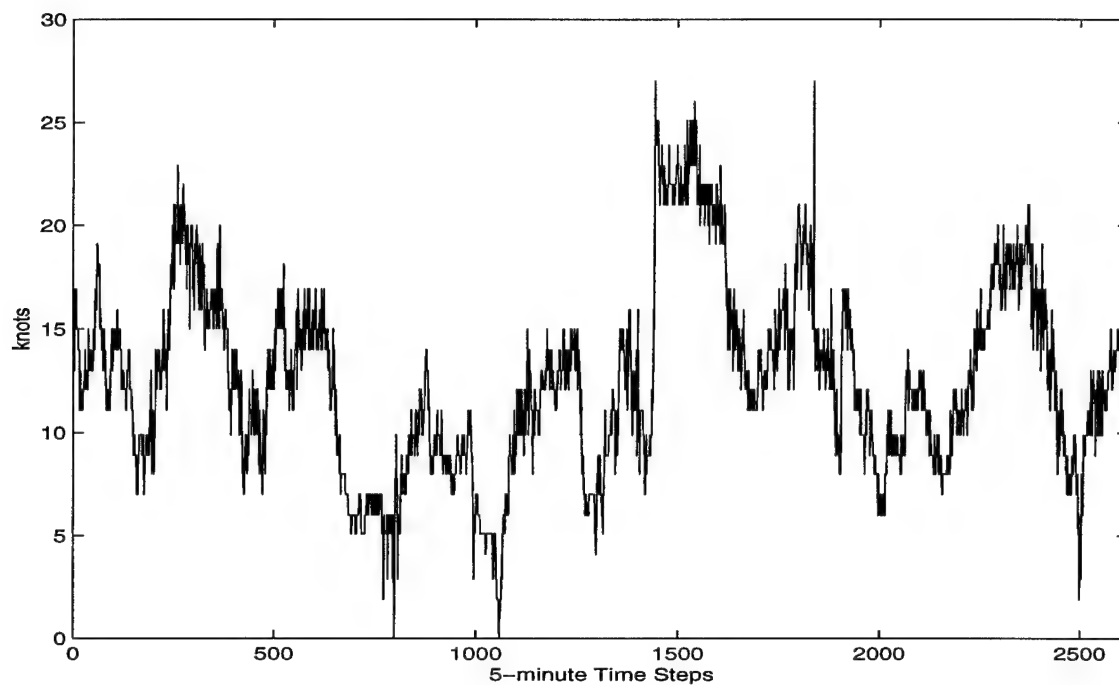


Figure A.14. 5-minute Peak Wind Speed, 1-10 March 1997.

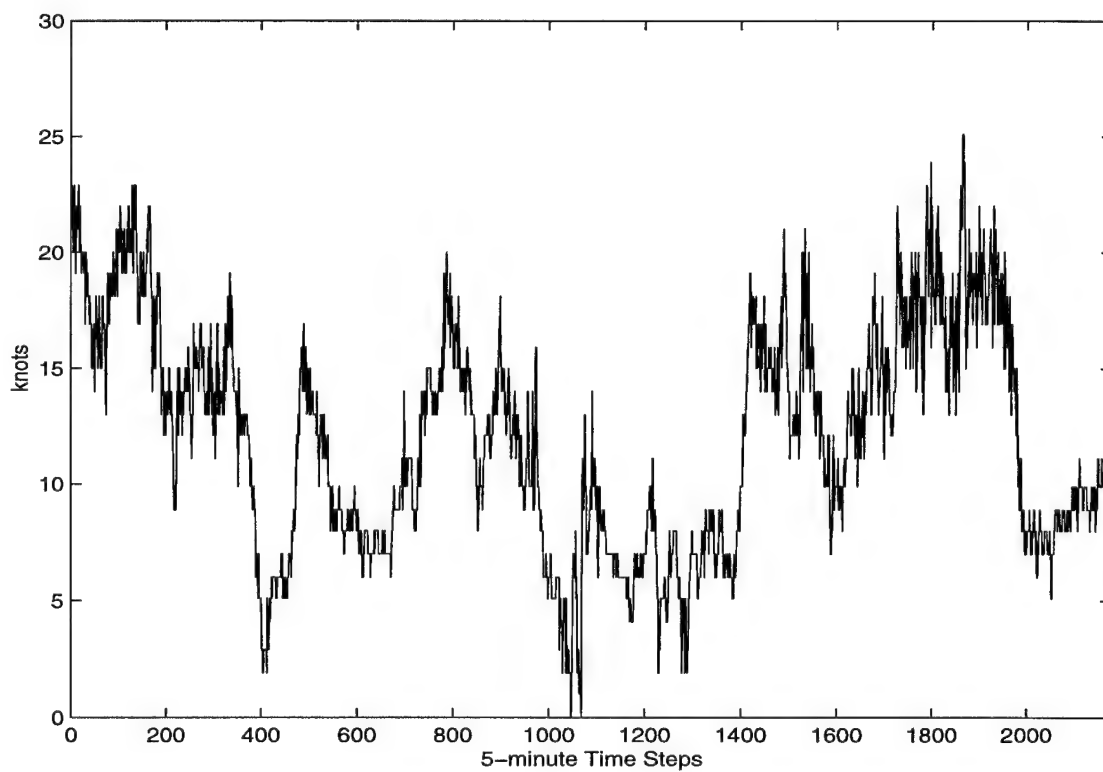


Figure A.15. 5-minute Peak Wind Speed, 25 November – 2 December 1997.

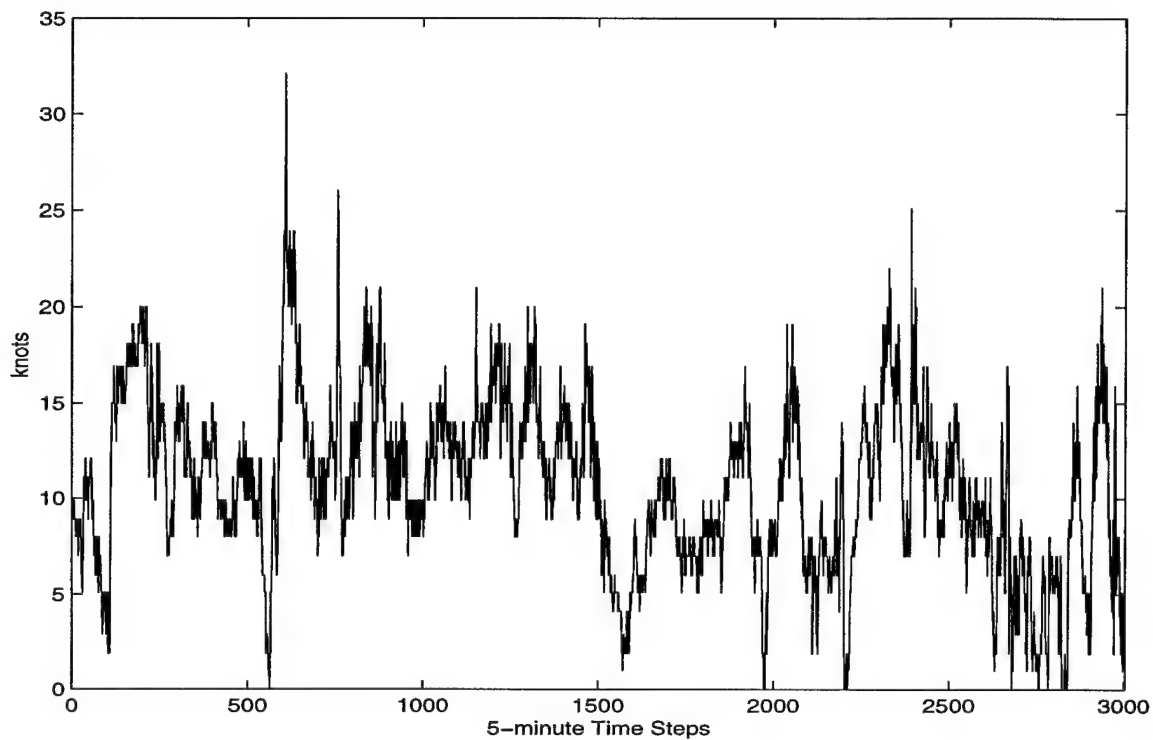


Figure A.16. 5-minute Peak Wind Speed, 2-13 December 1997.

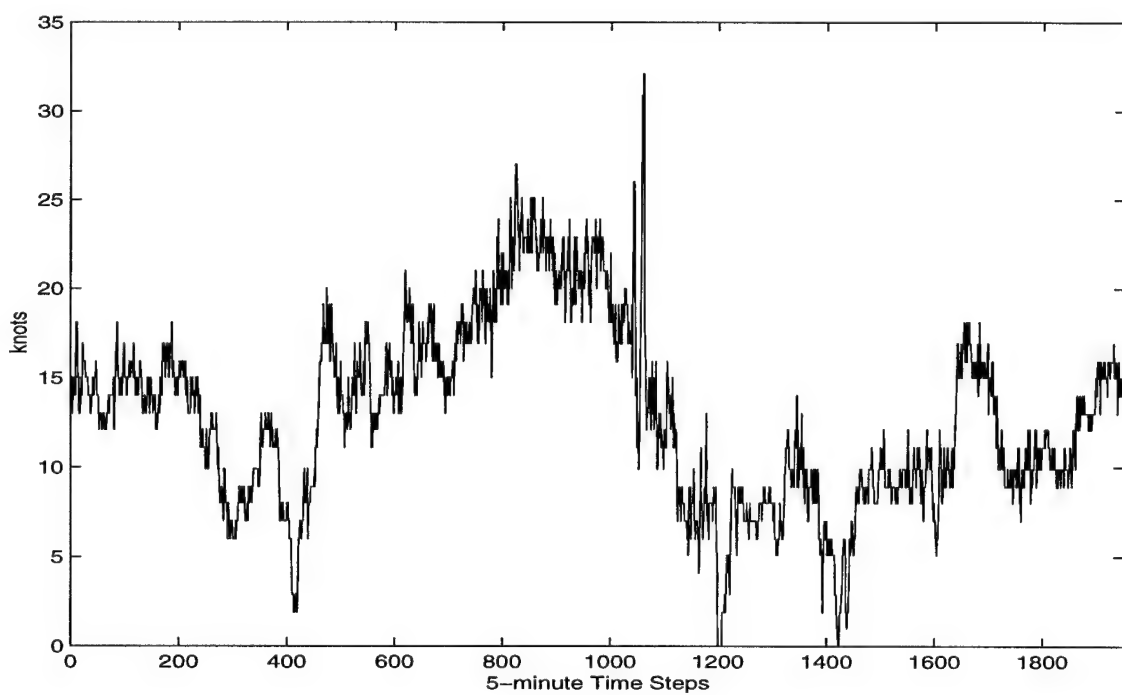


Figure A.17. 5-minute Peak Wind Speed, 5-11 January 1998.

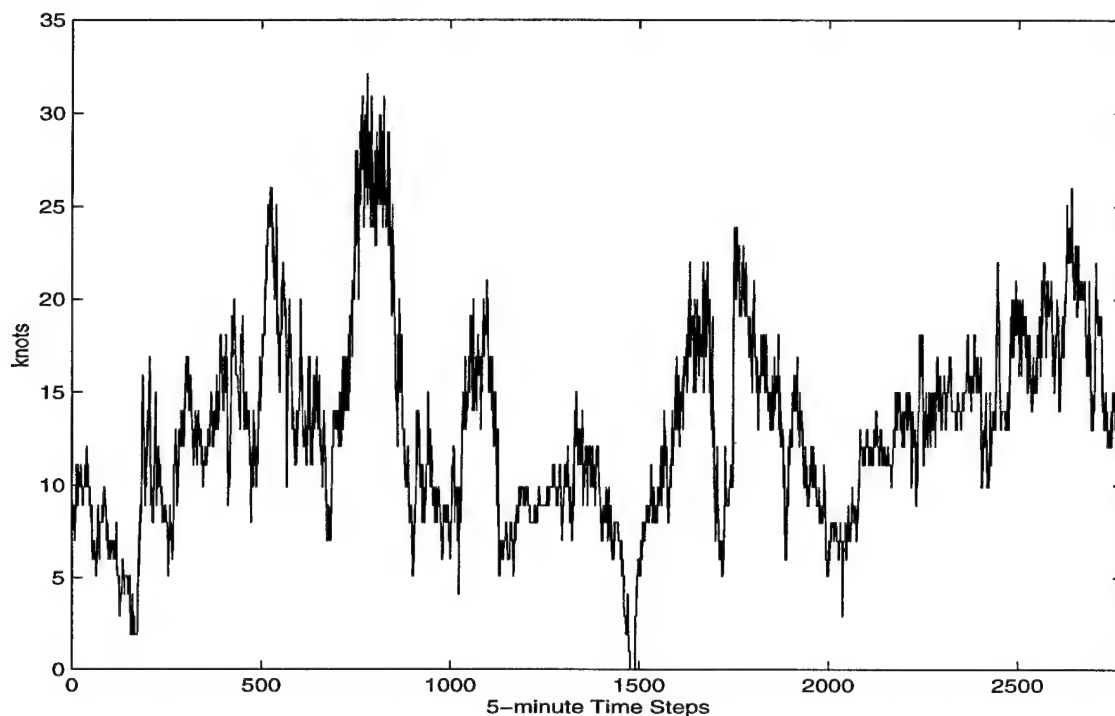


Figure A.18. 5-minute Peak Wind Speed, 14-23 January 1998.

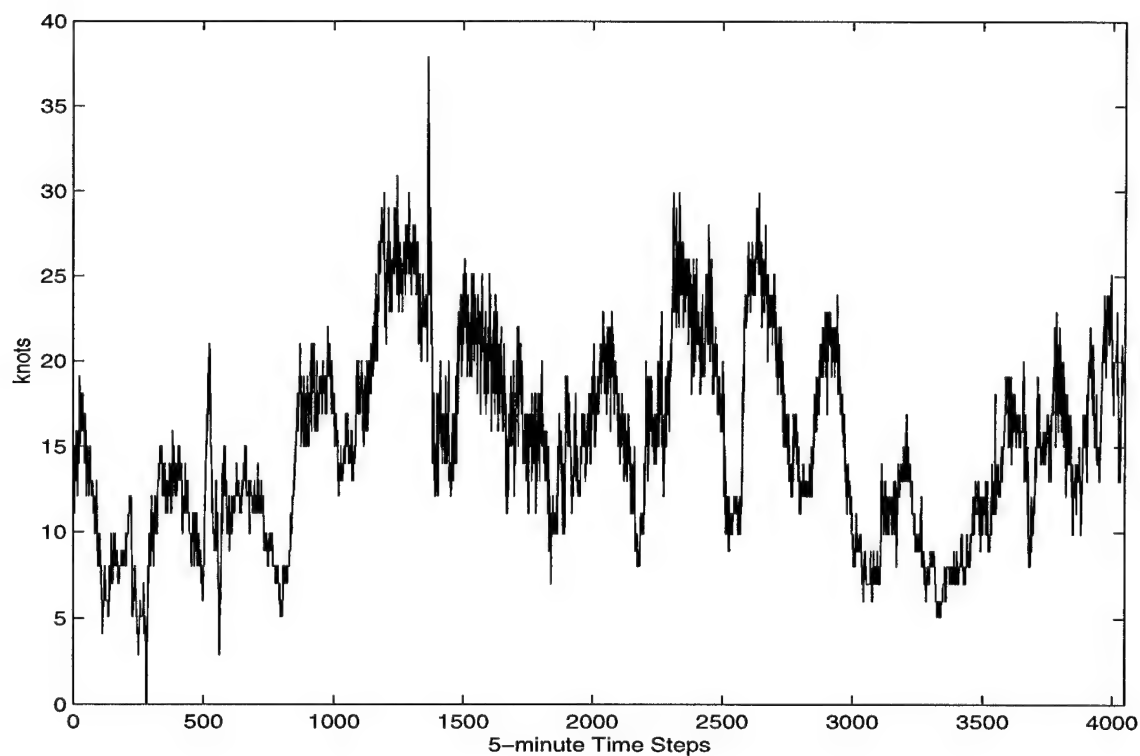


Figure A.19. 5-minute Peak Wind Speed, 4-18 March 1998.

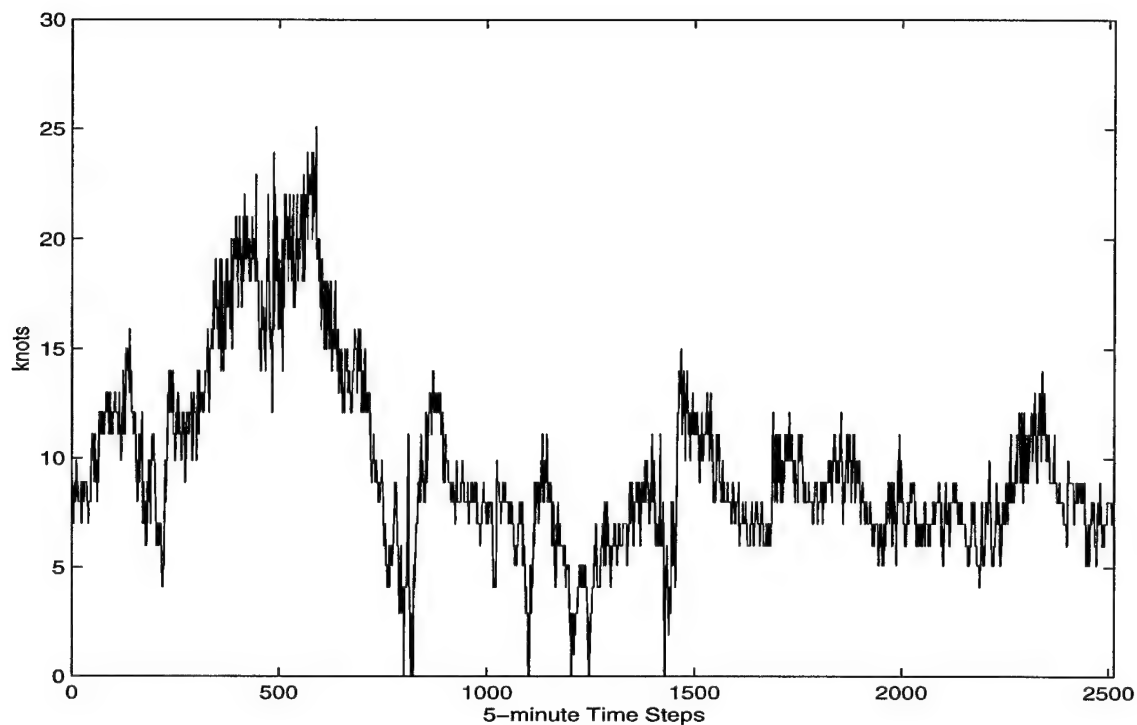


Figure A.20. 5-minute Peak Wind Speed, 8-17 November 1998.

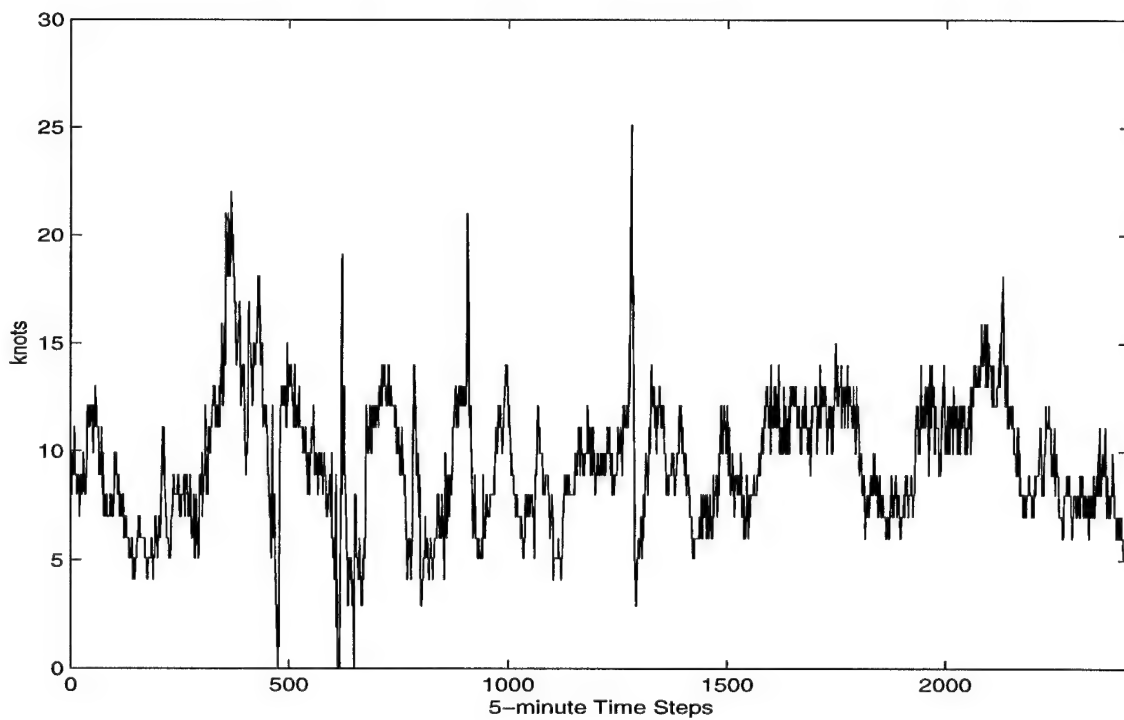


Figure A.21. 5-minute Peak Wind Speed, 30 November – 8 December 1998.

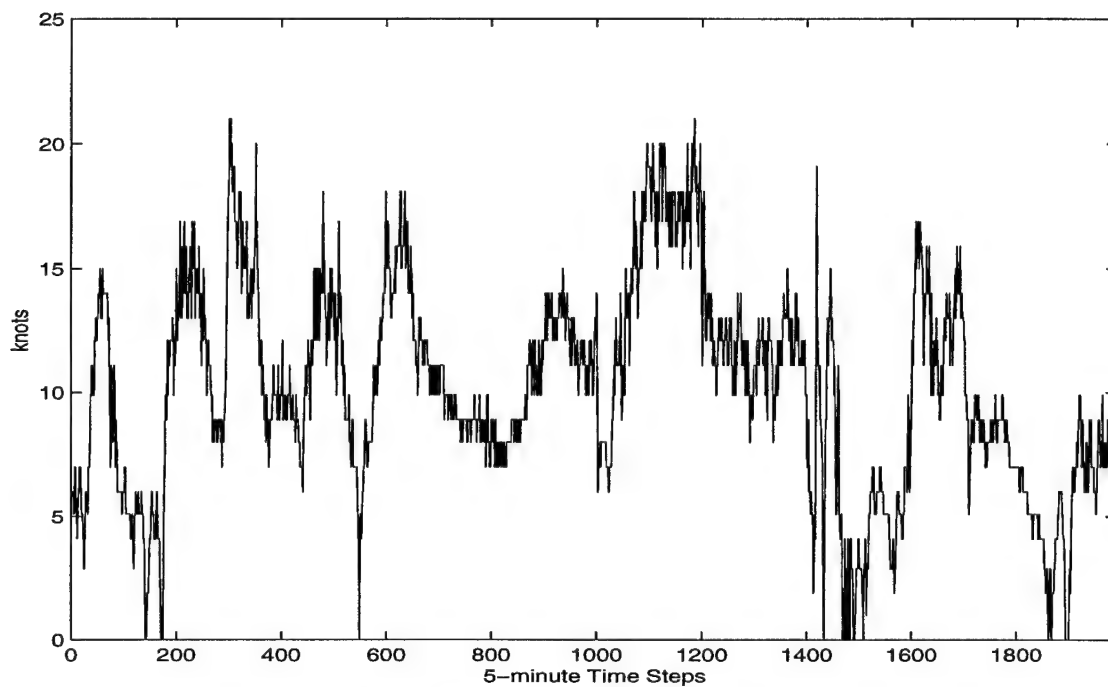


Figure A.22. 5-minute Peak Wind Speed, 14-20 January 1999.

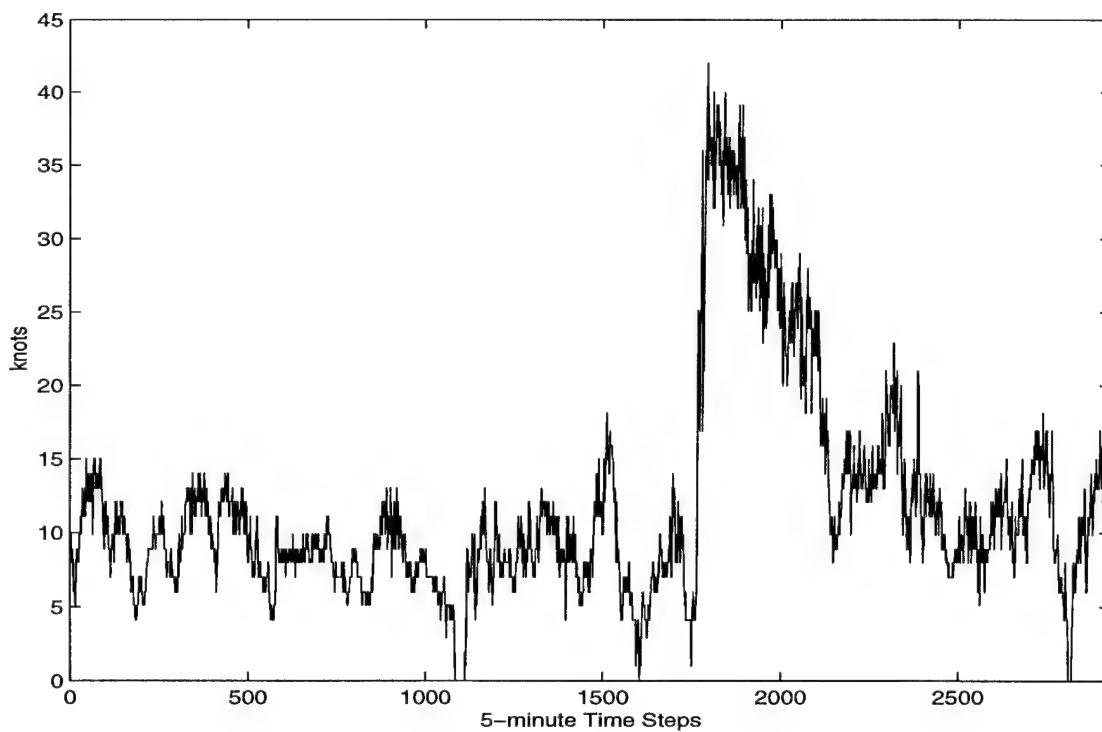


Figure A.23. 5-minute Peak Wind Speed, 25 January – 4 February 1999.

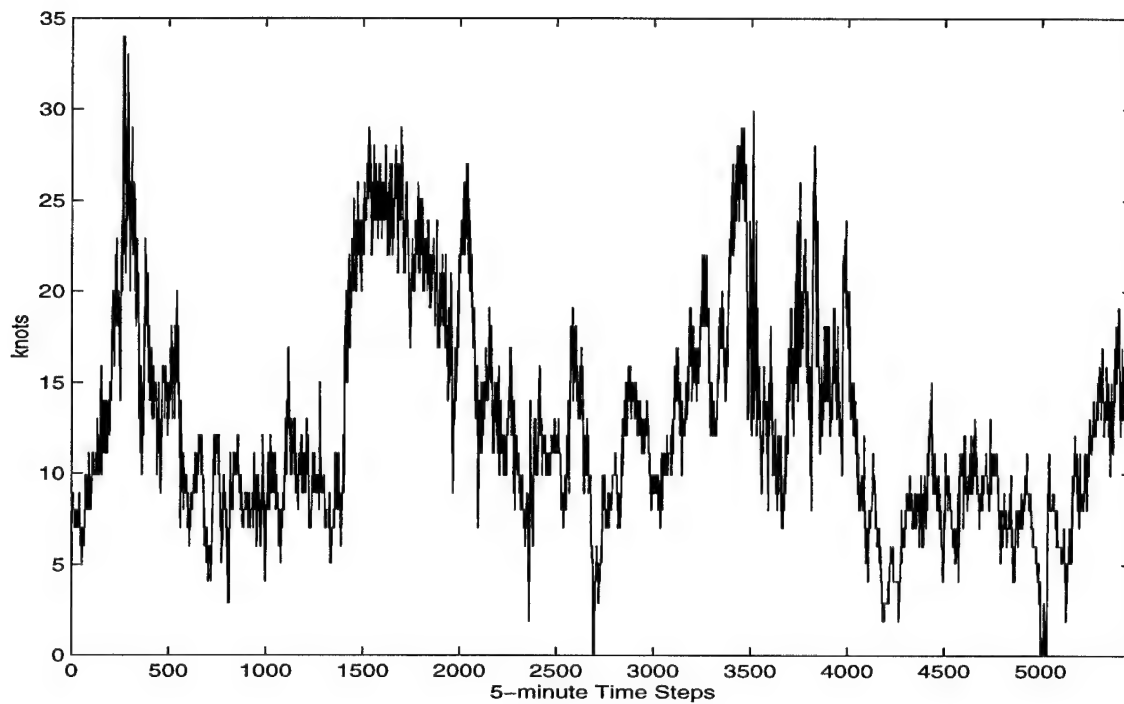


Figure A.24. 5-minute Peak Wind Speed, 2-21 March 1999.

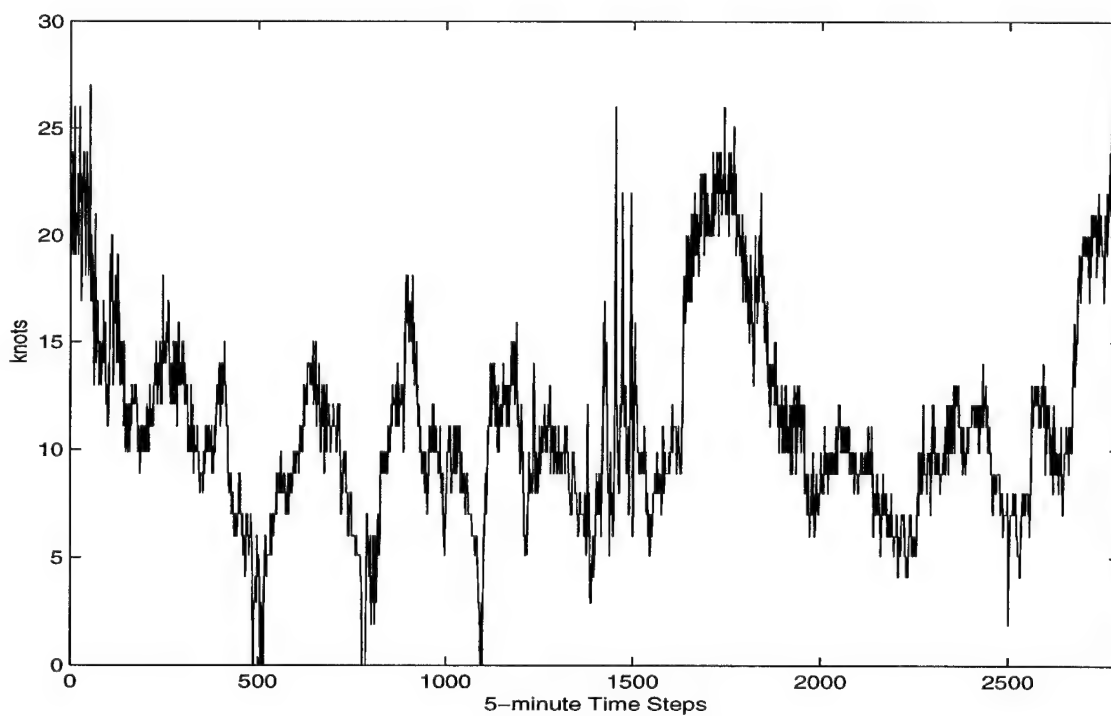


Figure A.25. 5-minute Peak Wind Speed, 21-31 March 1999.

Appendix B: Period of Record Data Gaps

This appendix contains a complete list of gaps in the database available for this study.

The 25 longest periods with *no* gaps (marked with a * in the table) were used in this research.

Table B.1. Period of Record Data Gaps

Julian Date	Time of Day	# Gaps
95045	0-415	52
95045	1135-1145	3
95045	1315-1335	5
95051	1550-1855	38
95053	1920-2355	45
95054	0-2355	288
95055	0-1725	211
95057	35-45	3
95057	1845-1950	14
95058	0-2355	288
95061	1620-2010	49
*		
95071	55-115	5
95074	2225-2355	19
95078	525	1
*		
95085	2330-2355	6
95086	0-1110	133
95086	1255	1
95086	1300	1
95086	1305-1315	3
95086	1320-1930	75
95087	1055-1255	24
95087	1630	1
95088	1330-1340	3
95089	1440-1610	30
95090	2325-2355	7
95309	1425-1440	4
*		
95317	1410-1430	5
95321	2210-2355	46
95322	0-130	19
95325	1355-2355	121

Julian Date	Time of Day	# Gaps
95326	0-1335	163
95328	855-2355	181
95329	0-405	50
95329	410-2355	238
95330	0	1
95330	1605-1620	4
95331	1140-1210	7
95332	2135	1
*		
95339	1435	1
*		
95347	30	1
95349	1630-1645	4
95350	1915-1925	3
95353	1155	1
95353	1840-2355	65
95355	5-1130	137
95361	0-255	37
96001	1445-1535	11
96004	1435-1450	4
96004	1755-1805	3
96004	1830-1845	4
96006	1935	1
96007	120	1
96010	1305-1420	16
96010	1425-1455	7
96010	1500-2020	66
96016	1420-1450	7
96024	330	1
*		
96032	1325-1340	4
96032	1445	1
96034	1330-1435	14

Julian Date	Time of Day	# Gaps
96041	1325-2235	110
96042	1705	1
96042	2005-2320	40
*		
96053	0-2355	288
*		
96068	0-2355	288
96072	2305-2355	11
96074	2355	1
*		
96312	1135-1140	2
96312	1205-1210	2
96315	1825-1850	6
96315	1900-1910	3
96316	2145-2210	6
96320	355-430	8
96321	815-1115	37
96322	230	1
96323	1915	1
96327	1555	1
96327	1855-2055	25
96328	1845	1
96331	0-2355	288
*		
96343	1305-1340	8
96346	0-2355	288
96347	0-2355	288
96349	1925	1
*		
96357	1815-1820	2
96357	2055	1
96359	1740-1905	19
96361	1010-2355	167
96362	0-500	61
96362	1700-1825	19
96363	1950-2005	4
96366	215-435	29
96366	1700-1810	15
97001	0-200	25
97002	1525-1600	8
97002	1730-1755	6
97003	1555-1605	3
97003	1615-1635	5
97006	1725	1

Julian Date	Time of Day	# Gaps
*		
97021	2320	1
97023	1400-1405	2
97023	1430-1450	5
97027	1530-1540	3
97029	1230-1250	5
*		
97037	1700	1
97038	1355	1
97038	1430-1445	4
97044	5-300	36
97044	1250-1300	3
97044	1320	1
97044	1335-1350	4
97048	1525-2355	103
97051	1415	1
97053	1935-2010	8
97054	1520-1650	19
97057	1440	1
97059	2315-2355	9
97060	0-2100	253
*		
97069	2330-2355	6
97070	2355	1
97073	1610	1
97076	1225-1305	7
97077	2100	1
97082	5-120	16
97085	1410-1420	3
97085	1700-1725	6
97311	1125-1215	11
97315	900-1350	59
97318	935-2355	174
97319	0-600	73
97321	1315-1330	4
97327	115-120	2
97328	35-2355	280
*		
97336	1330-1345	4
*		
97347	5-1415	171
97350	1535-1605	7
97356	1530	1
97357	245-805	65

Julian Date	Time of Day	# Gaps
97363	1325-1350	6
98004	2250-2355	14
*		
98011	1845-1850	2
98012	10	1
98012	45	1
98012	1320-1335	4
98013	1455-2355	109
*		
98023	1550	1
98024	2040	1
98027	1320-1345	6
98027	1510-1630	17
98028	1300-1315	4
98029	1215	1
98031	310-350	9
98032	1525-2355	104
98033	0-1440	178
98033	1600-1700	13
98037	1845-2355	63
98038	0-1510	183
98039	135	1
98042	1205-1230	6
98043	1415-1445	7
98046	1910-1950	9
98046	2045	1
98050	1010-1025	4
98055	1710-2000	35
98061	1700-1955	36
98062	1500	1
98063	1320-1400	9
*		
98077	1525-1540	4
98079	1045-1135	11
98079	1625-1715	11
98079	1735	1
98080	2355	1
98081	2355	1
98084	1305-1420	16
98085	1300-1315	4
98085	2335-2355	5
98090	5-230	31
98308	1215-1310	12
98312	1815-1835	5

Julian Date	Time of Day	# Gaps
*		
98321	1230-1325	12
98325	2035	1
98325	2350-2355	2
98326	0	1
98326	15	1
98327	1150-2355	146
98328	0-2355	288
98329	0-2355	288
98330	0-2355	288
98331	1420-1425	2
98331	1810-1840	7
98333	2030	1
98334	1220-1410	23
*		
98343	0-2355	288
98345	1310-1330	5
98349	1535-1555	5
98349	1625-1650	6
98352	1120-1150	7
98356	1120-1140	5
98358	1325-1415	11
99005	1900	1
99005	2000	1
99009	1355-1425	7
99009	1540-1735	24
99013	0-2355	288
*		
99020	2200-2245	10
99020	2300	1
99020	2315-2355	9
99023	1410	1
99023	1825-1845	5
99023	1910	1
99023	1935-1940	2
99023	2025-2030	2
99023	2050-2110	5
99023	2350	1
99024	230	1
99024	835	1
99024	1830-1840	3
99025	1345	1
*		
99035	1800-1940	21

Julian Date	Time of Day	# Gaps
99036	1210-1225	4
99036	1815-1835	5
99036	2005	1
99036	2025-2100	8
99039	0-2355	288
99041	2110-2125	4
99041	2205-2335	20
99042	5-1605	193
99042	1635	1
99042	2000	1
99042	2020-2030	3
99042	2230-2305	8
99042	2335-2355	5
99043	0-230	32
99043	1235	1
99043	1255-1305	3
99043	1320-1405	10
99043	1530	1
99045	1820	1
99046	1755	1
99048	2155	1
99050	1315-1330	4
99051	1240-1315	8
99051	1515-1605	11
99053	1600-1615	4
99056	1325	1
99056	2305	1
99057	2000-2130	19
99061	1700-1755	12
*		
99080	1810	1
*		
99090	1140-1200	5

Appendix C: MATLAB Program Codes

This appendix contains the five MATLAB “m-file” programs used to develop, train, test, and evaluate the neural network.

% development.m Capt Kenneth P. Cloys 8 Jan 00

```
load tx96075_91.txt;
transfer = tx96075_91;

sinetime = sin(transfer(:,2)*2*pi/2355); sinedir = sin(transfer(:,3)*2*pi/360);

speed = transfer(:,4)'; pk = transfer(:,5)'; dirdev = transfer(:,6)';
delta1 = diff(pk); delta2 = diff(delta1);

b = (1/12)*ones(1,12);
smpk = filter(b,1,pk); smdir = filter(b,1,sinedir); smdirdev = filter(b,1,dirdev);
smdelta1 = filter(b,1,delta1); smdelta2 = filter(b,1,delta2); smtime = filter(b,1,sinetime);

for j = 1:length(transfer)-9
    mx30(j) = max(pk(j+3:j+9));
end;

minneurons = 11; maxneurons = 14; mindelays = 12; maxdelays = 36;

trainstart = 50; trast = trainstart;
% Specifies time step at which to start training.
% If neither delta is used, 'trainstart' must be at least d+1;
% if only d1 used, at least d+2; if delta2 used, at least d+3.

blocksize = 250; bs = blocksize;
% Specifies how many time steps to train with during each training iteration.

numblocks = 2;
% Specifies how many training iterations to make.
% Alternatively, 'trainlength' can be specified and 'numblocks'
% computed with 'numblocks = trainlength/blocksize'.
% If 'numblocks' is to be computed, however, it must follow
% the line specifying the value of 'trainlength'.

trainlength = blocksize*numblocks;
% Specifies how many total time steps are to be trained on.
```

```

% If 'blocksize' & 'numblocks' are specified, 'trainlength' is computed from them.
% If computing 'numblocks' from 'trainlength', 'trainlength' must be evenly divisible by
% 'blocksize'.
% 'trainstart+trainlength' must be less than length(transfer),
% the last time step of the input vector.

teststart = 1100; tstst = teststart;
% Specifies time step at which to start testing the net on new inputs.
% See notes above for 'trainstart' regarding minimum value.

testlength = 500;
% Specifies how many total time steps are to be tested.

testend = teststart + testlength;
% Specifies time step at which to stop testing.
% Must be less than length(transfer)-9.

fcstperiods = [1;2;3;4;5;6;7;8;9;10;11;12;13;14;15;16]; fp = fcstperiods;
% Specifies which half-hour periods to forecast for.

row = 1;

for i = 1:16
    verify{i} = mx30(tstst+6*(i-1):testend+6*(i-1));
end; %Creates verification vector for comparison with forecasts and persistence.

pers = mx30(teststart-9:testend-9);
% Creates persistence vector for comparison with verification.

for d = mindelays:12:maxdelays;
    for n = minneurons:maxneurons;

        net = newfftd([minmax(pk); minmax(smdelta1); minmax(smdelta2); ...
            -1 1; -1 1; minmax(smdirdev)], [0:12:d],[n 16],{'tansig' 'purelin'});

        net.trainParam.epochs = 10; net.trainParam.goal = .1; net.trainParam.show = 1;

        for nb = 1:numblocks
            A = (nb-1)*bs+trast;

            Pi = con2seq([smpk(A-d:A-1); smdelta1(A-d:A-1); smdelta2(A-d:A-1); ...
                smdir(A-d:A-1); smtime(A-d:A-1); smdirdev(A-d:A-1)]);

            P = con2seq([smpk(A:A+bs-1); smdelta1(A:A+bs-1); smdelta2(A:A+bs-1); ...
                smdir(A:A+bs-1); smtime(A:A+bs-1); smdirdev(A:A+bs-1)]);

```

```

T = con2seq([mx30(A:A+bs-1); mx30(A+6:A+bs+5); mx30(A+12:A+bs+11); ...
            mx30(A+18:A+bs+17); mx30(A+24:A+bs+23); mx30(A+30:A+bs+29); ...
            mx30(A+36:A+bs+35); mx30(A+42:A+bs+41); mx30(A+48:A+bs+47); ...
            mx30(A+54:A+bs+53); mx30(A+60:A+bs+59); mx30(A+66:A+bs+65); ...
            mx30(A+72:A+bs+71); mx30(A+78:A+bs+77); mx30(A+84:A+bs+83); ...
            mx30(A+90:A+bs+89)]);

format compact;
['neurons ','delays ','blocknumber']
[int2str(n),' of ',int2str(maxneurons),' ',int2str(d),' of ',int2str(maxdelays), ...
 ' ',int2str(nb),' of ',int2str(numblocks)]

net = train(net,P,T,Pi);
end;

Ri = con2seq([smpk(tstst-d:tstst-1); smdelta1(tstst-d:tstst-1); smdelta2(tstst-d:tstst-1);
smdir(tstst-d:tstst-1); smtime(tstst-d:tstst-1); smdirdev(tstst-d:tstst-1)]);

R = con2seq([smpk(tstst:testend); smdelta1(tstst:testend); smdelta2(tstst:testend);
smdir(tstst:testend); smtime(tstst:testend); smdirdev(tstst:testend)]);

Y = sim(net,R,Ri); y = seq2con(Y);

numfcsts = length(fp);

for s = 1:numfcsts
    fcst{s} = y{1}(s,:);
    rep96075_91wx(row,1) = n;
    rep96075_91wx(row,2) = d;
    rep96075_91wx(row,3) = s*.5; %Time.
    rep96075_91wx(row,4) = mae(fcst{s}-verify{fp(s)});
    rep96075_91wx(row,5) = mae(pers-verify{fp(s)});
    rep96075_91wx(row,6) = mse(fcst{s}-verify{fp(s)});
    rep96075_91wx(row,7) = mse(pers-verify{fp(s)});
    rep96075_91wx(row,8) = max(fcst{s}-verify{fp(s)});
    rep96075_91wx(row,9) = max(pers-verify{fp(s)});
    [fm,fb,rep96075_91wx(row,10)] = postreg(fcst{s},verify{fp(s)});
    [pm,pb,rep96075_91wx(row,11)] = postreg(pers,verify{fp(s)});
    row = row+1;
end;
save report96075_91wx2 rep96075_91wx
printmat(rep96075_91wx,'nil',int2str(1:row-1), ...
'neurons delays vt fcstmae persmae fcstmse persmse fmaxerr persmaxerr fcstr persr')
end; end;

```

% nntrain3.m Capt Kenneth P. Cloys 8 Jan 00

% For more training run 'nnnext.m' after this.

```
load tx99025_35.txt;
transfer = tx99025_35;
```

```
sinetime = sin(transfer(:,2)*2*pi/2355);
sinedir = sin(transfer(:,3)*2*pi/360);
```

```
pk = transfer(:,5); dirdev = transfer(:,6);
delta1 = diff(pk); delta2 = diff(delta1);
```

```
for j = 1:length(transfer)-9
    mx30(j) = max(pk(j+3:j+9));
end;
```

```
b = (1/12)*ones(1,12);
```

```
smpk = filter(b,1,pk); smdir = filter(b,1,sinedir); smdirdev = filter(b,1,dirdev);
smdelta2 = filter(b,1,delta2);
smtime = filter(b,1,sinetime); smmx30 = filter(b,1,mx30);
```

```
neurons = 10; n = neurons;
delays = 36; d = delays;
```

```
trainstart = 51; trast = trainstart;
% Specifies time step at which to start training.
% If neither delta is used, 'trainstart' must be at least d+1.
% If only delta1, at least d+2; if delta2 used, at least d+3.
```

```
blocksize = 250; bs = blocksize;
% Specifies how many time steps to train with during each block of training.
```

```
numblocks = 4;
% Specifies how many training iterations to make.
```

```
% Alternatively, 'trainlength' can be specified and 'numblocks'
% computed with 'numblocks = trainlength/blocksize'.
```

```
% If 'numblocks' is to be computed, however, it must follow
% the line specifying the value of 'trainlength'.
```

```

trainlength = blocksize*numblocks;
% Specifies how many total time steps are to be trained on.

% If 'blocksize' & 'numblocks' are specified, 'trainlength'
% is computed from them.

% If computing 'numblocks' from 'trainlength', 'trainlength'
% must be evenly divisible by 'blocksize'.

% 'trainstart+trainlength' must be less than 'length(transfer)-99'.

net = newfftd([minmax(mx30); minmax(pk); minmax(smdelta2); ...
    -1 1; -1 1; minmax(smdirdev)], [0:12:d],[n 16],{'tansig' 'purelin'});

net.trainParam.epochs = 20; net.trainParam.goal = .1; net.trainParam.show = 1;

for nb = 1:numblocks
    A = (nb-1)*bs+trast;

    Pi = con2seq([smtx30(A-d-6:A-7);smpk(A-d:A-1); ...
        smdelta2(A-d:A-1); smdir(A-d:A-1); smtime(A-d:A-1); smdirdev(A-d:A-1)]);

    P = con2seq([smtx30(A-6:A+bs-7); smpk(A:A+bs-1); ...
        smdelta2(A:A+bs-1); smdir(A:A+bs-1); smtime(A:A+bs-1); smdirdev(A:A+bs-1)]);

    T = con2seq([mtx30(A:A+bs-1); mx30(A+6:A+bs+5); mx30(A+12:A+bs+11); ...
        mx30(A+18:A+bs+17); mx30(A+24:A+bs+23); mx30(A+30:A+bs+29); ...
        mx30(A+36:A+bs+35); mx30(A+42:A+bs+41); mx30(A+48:A+bs+47); ...
        mx30(A+54:A+bs+53); mx30(A+60:A+bs+59); mx30(A+66:A+bs+65); ...
        mx30(A+72:A+bs+71); mx30(A+78:A+bs+77); mx30(A+84:A+bs+83); ...
        mx30(A+90:A+bs+89)]);

    net = train(net,P,T,Pi);
end;

netn = net;
save config99025_35 net;

```

% nnnext.m 8 Jan 00 Capt Kenneth P. Cloys

% For training NN on inputs beyond those used during NN set-up and initial training
% in 'nntrain3.m'.

% Training starts with weights and biases obtained with 'nntrain3.m' or previous runs
% of the present file and updates the weights and biases as often as the present file is run.

% To train on different data files, substitute desired data file name in next line.

load tx96024_32.txt; transfer = tx96024_32;

sinetime = sin(transfer(:,2)*2*pi/2355); sinedir = sin(transfer(:,3)*2*pi/360);
% Normalizes values of time and wind direction between -1 and 1.
% Removes problem of jumping 2355->0 and 355->0.

pk = transfer(:,5); dirdev = transfer(:,6); delta1 = diff(pk); delta2 = diff(delta1);
% 'delta1' is vector of differences in successive values of peak wind speed.
% 'delta2' is vector of differences in successive values of 'delta1'.

b = (1/12)*ones(1,12);
% Denominator in first parenthesis and last number in second parenthesis
% (which must be the same number) specifies number of time steps to average over
% in creating the moving-average 'sm_____' input vectors below.

smpk = filter(b,1,pk); smdir = filter(b,1,sinedir); smdirdev = filter(b,1,dirdev);
smdelta1 = filter(b,1,delta1); smdelta2 = filter(b,1,delta2); smtime = filter(b,1,sinetime);

for j = 1:length(transfer)-9
 mx30(j) = max(pk(j+3:j+9));
end;
% Creates vector of 30-minute maximum peak winds. Used to generate target vector.

trainstart = 100; trast = trainstart;
% Specifies time step at which to start training.
% If neither 'delta1' nor 'delta2' is used, 'trainstart' must be at least 1 more than the
% number of delays used. If only 'delta1' is used, 'trainstart' must be at least 2 more than the
% number of delays; if 'delta2' is used, at least 3 more than the number of delays.

blocksize = 250; bs = blocksize;
% Specifies how many time steps to train with during each training iteration.
% Dividing the training set into smaller blocks helps keep the processor from bogging down
% or locking the system completely.

numblocks = 8;
% Specifies how many training iterations to make.

```

trainlength = blocksize * numblocks;
% Total number of time steps to be used in updating the net.

% Alternatively, 'trainlength' can be specified and 'numblocks'
% computed with 'numblocks = trainlength/blocksize'.

% If 'numblocks' is to be computed, however (as opposed to being specified by the user),
% it must follow the line specifying the value of 'trainlength',
% which must be evenly divisible by 'blocksize'.

% If 'blocksize' & 'numblocks' are specified, 'trainlength' is computed from them.

% 'trainstart + trainlength' must be less than (number input file time steps - 99)
% in order to avoid trying to compute 'mx30' values from outside the range of data.

netn.trainParam.epochs = 20; netn.trainParam.goal = .1; netn.trainParam.show = 1;
for nb = 1:numblocks

    A = (nb-1)*bs+trast;
    % 'A' is an algebraic convenience.
    % Its use permits more compact specifications for 'Pi', 'P', and 'T'.

    Pi = con2seq([smpk(A-d:A-1); smdelta1(A-d:A-1); smdelta2(A-d:A-1); ...
        smdir(A-d:A-1); smtime(A-d:A-1); smdirdev(A-d:A-1)]);
    % Initial input delay values.

    P = con2seq([smpk(A:A+bs-1); smdelta1(A:A+bs-1); smdelta2(A:A+bs-1); ...
        smdir(A:A+bs-1); smtime(A:A+bs-1); smdirdev(A:A+bs-1)]);
    % Training inputs: Moving averages of various elements measured directly
    % by WINDS or derived from such measurements.

    T = con2seq([mx30(A:A+bs-1); mx30(A+6:A+bs+5); mx30(A+12:A+bs+11); ...
        mx30(A+18:A+bs+17); mx30(A+24:A+bs+23); mx30(A+30:A+bs+29); ...
        mx30(A+36:A+bs+35); mx30(A+42:A+bs+41); mx30(A+48:A+bs+47); ...
        mx30(A+54:A+bs+53); mx30(A+60:A+bs+59); mx30(A+66:A+bs+65); ...
        mx30(A+72:A+bs+71); mx30(A+78:A+bs+77); mx30(A+84:A+bs+83); ...
        mx30(A+90:A+bs+89)]);
    % Target vectors associated with training input vectors specified above.
    % 'T' is comprised of 16 30-minute maximum peak winds centered at 0:30, 1:00,
    % 1:30,..., 8:00 from the current 'P' input.
    netn = train(netn,P,T,Pi);
    % Updates previous network (weights and biases) using new inputs and targets.
end;
% For further training, this file can be run repeatedly with the same input data file
% with (a) different data file(s).

```

% nntest.m Capt Kenneth P. Cloys 8 Jan 00

```
load tx95339_47.txt; transfer = tx95339_47; load climo_mx30.txt; period = '95339_47';
sinetime = sin(transfer(:,2)*2*pi/2355); sinedir = sin(transfer(:,3)*2*pi/360);
pk = transfer(:,5); dirdev = transfer(:,6); delta1 = diff(pk); delta2 = diff(delta1);
```

```
b = (1/12)*ones(1,12); smpk = filter(b,1,pk); smdir = filter(b,1,sinedir);
smdirdev = filter(b,1,dirdev); smdelta2 = filter(b,1,delta2); smtime = filter(b,1,sinetime);
```

```
for j = 1:length(transfer)-9
    mx30(j) = max(pk(j+3:j+9));
end;
```

```
testlength = 250;
% Specifies how many total time steps are to be tested.
```

```
teststart = 49+unidrnd(length(transfer)-testlength-149)
tstst = teststart;
% Generates random time step at which to start testing the net on new inputs.
```

```
% If neither delta is used, 'teststart' must be at least d+1;
% if only d1 used, at least d+2; if delta2 used, at least d+3.
```

```
% This is to avoid trying to compute input vectors using values from
% before the period covered by the database.
```

```
timeofday = transfer(tstst,2)
climoseed = find(climo_mx30(:,1)==timeofday)
% Index (row number) in 'climo_mx30' corresponding to time-of-day of 'teststart'.
% Specifies "current" time in 'climo_mx30' and determines which values
% in 'climo_mx30' to use as climatological forecasts.
```

```
% 'climo_mx30' repeats itself after 2355, so 'teststart' values corresponding to times near the
% end of the day do not present a problem for creating the 'climo' vector later.
```

```
% 'teststart' value --> input vector time-of-day --> 'climo_mx30' time-of-day --> 'climo_mx30'
% value
```

```
testend = teststart + testlength-1;
% Specifies time step at which to stop testing. Must be less than length(transfer)-99 in order to
% avoid trying to compute 'mx30' values from after the period covered by the database.
```

```
fcstperiods = [1;2;3;4;5;6;7;8;9;10;11;12;13;14;15;16]; fp = fcstperiods;
% Specifies which half-hour periods to forecast for.
```

```
% numfcsts = length(fp);
```



```

row = 1;

pers = mx30(teststart-9:testend-9);
% Creates persistence vector for comparison with verification.

Ri = con2seq([smpk(tstst-d:tstst-1); smdelta1(tstst-d:tstst-1); smdelta2(tstst-d:tstst-1);
    smdir(tstst-d:tstst-1); smtime(tstst-d:tstst-1); smdirdev(tstst-d:tstst-1)]);

R = con2seq([smpk(tstst:testend); smdelta1(tstst:testend); smdelta2(tstst:testend);
    dir(tstst:testend); smtime(tstst:testend); smdirdev(tstst:testend)]);

Y = sim(netn,R,Ri); y = seq2con(Y);
for s = 1:16
    random = gamrnd(4.9308,2.5568,1,testlength);
    verify{s} = mx30(tstst+6*(s-1):testend+6*(s-1));
    climo(s,1:testlength) = climo_mx30(climoseed(1)+6*s,2);
    % Creates verification and climatology vectors for comparison with
    % forecasts and persistence.
    fcst{s} = y{1}(s,:);
    rep95339_47(row,1) = n;
    rep95339_47(row,2) = d;
    rep95339_47(row,3) = s*.5; % Forecast Time.
    rep95339_47(row,4) = mae(fcst{s}-verify{fp(s)});
    rep95339_47(row,5) = mae(pers-verify{fp(s)});
    rep95339_47(row,6) = mae(climo(s,:)-verify{fp(s)});
    rep95339_47(row,7) = mae(random-verify{fp(s)});
    rep95339_47(row,8) = mse(fcst{s}-verify{fp(s)});
    rep95339_47(row,9) = mse(pers-verify{fp(s)});
    rep95339_47(row,10) = mse(climo(s,:)-verify{fp(s)});
    rep95339_47(row,11) = mse(random-verify{fp(s)});
    rep95339_47(row,12) = max(fcst{s}-verify{fp(s)});
    rep95339_47(row,13) = max(pers-verify{fp(s)});
    rep95339_47(row,14) = max(climo(s,:)-verify{fp(s)});
    rep95339_47(row,15) = max(random-verify{fp(s)});
    [fm,fb,rep95339_47(row,16)] = postreg(fcst{s},verify{fp(s)});
    [pm,pb,rep95339_47(row,17)] = postreg(pers,verify{fp(s)});
    % [cm,cb,rep95339_47(row,18)] = postreg(climo(s,:),verify{fp(s)});
    [rm,rb,rep95339_47(row,18)] = postreg(random,verify{fp(s)});
    pictures;
    row = row+1;
end;

printmat(rep95339_47,'nil',int2str(1:row-1), ...
    'neurons delays vt fcstmae persmae climomae randommae fcstmse persmse climomse
    randommse fcstmaxerr persmaxerr climomaxerr randommaxerr fcstr persr randomr')
save testrep95339_47 rep95339_47 -ascii

```

```

% pictures.m

figname = ['Fig' (period) '_' int2str(s)];

subplot(2,2,1); plot(fcst{s},'k'); hold on;
plot(verify{s},'k:');
plot(abs(fcst{s}-verify{s}),'k--');
plot(1:testlength,mean(abs(fcst{s}-verify{s})), 'k+')
%legend('Fcst','Obsv','Abs Err',-1);
xlabel('Forecasts'); ylabel('knots')
title(['Neural Net(-), Verification(..), MAE(--), ' ...
      'mean MAE(+), Forecast Hour: ' num2str(s*.5)])

subplot(2,2,2); plot(pers,'k'); hold on;
plot(verify{s},'k:');
plot(abs(pers-verify{s}),'k--');
plot(1:testlength,mean(abs(pers-verify{s})), 'k+')
%legend('Fcst','Obsv','Abs Err',-1);
xlabel('Forecasts'); ylabel('knots')
title(['Persistence(-), Verification(..), MAE(--), ' ...
      'mean MAE(+), Forecast Hour : ' num2str(s*.5)])

subplot(2,2,3); plot(climo(s,:), 'k'); hold on;
plot(verify{s},'k:');
plot(abs(climo(s,:)-verify{s}),'k--');
plot(1:testlength,mean(abs(climo(s,:)-verify{s})), 'k+')
%legend('Pers','Obsv','Abs Err',-1);
xlabel('Forecasts'); ylabel('knots')
title(['Climatology(-), Verification(..), MAE(--), ' ...
      'mean MAE(+), Forecast Hour: ' num2str(s*.5)])

subplot(2,2,4); plot(randum,'k'); hold on;
plot(verify{s},'k:');
plot(abs(randum-verify{s}),'k--');
plot(1:testlength,mean(abs(randum-verify{s})), 'k+')
%legend('Pers','Obsv','Abs Err',-1);
xlabel('Forecasts'); ylabel('knots')
title(['Random(-), Verification(..), MAE(--), ' ...
      'mean MAE(+), Forecast Hour: ' num2str(s*.5)])

print ( '-dmfile', figname)
print ( '-deps', '-tiff', figname)

```

```

% nntest3.m      5/6 Jan

load tx99025_35.txt; transfer = tx99025_35;
load climo_mx30.txt; period = '99025_35';
sinetime = sin(transfer(:,2)*2*pi/2355); sinedir = sin(transfer(:,3)*2*pi/360);
pk = transfer(:,5); dirdev = transfer(:,6); delta1 = diff(pk); delta2 = diff(delta1);

for j = 1:length(transfer)-9
    mx30(j) = max(pk(j+3:j+9));
end;

b = (1/12)*ones(1,12);

smpk = filter(b,1,pk); smdir = filter(b,1,sinedir); smdirdev = filter(b,1,dirdev);
smdelta1 = filter(b,1,delta1); smdelta2 = filter(b,1,delta2);
smtime = filter(b,1,sinetime); smmx30 = filter(b,1,mx30);

testlength = 100
% Specifies how many total time steps are to be tested.

teststart = 1100; tstst = teststart;
% Generates time step at which to start testing the net on new inputs.
% If neither delta is used, 'teststart' must be at least d+1; if only d1 used, at least d+2;
% if delta2 used, at least d+3.
% This is to avoid trying to compute input vectors using values from
% before the period covered by the database.

timeofday = transfer(tstst,2); climoseed = find(climo_mx30(:,1)==timeofday)
% Index (row number) in 'climo_mx30' corresponding to time-of-day of 'teststart'.
% Specifies "current" time in 'climo_mx30' and determines which values
% in 'climo_mx30' to use as climatological forecasts.
% 'climo_mx30' repeats itself after 2355, so 'teststart' values corresponding to
% times near the end of the day do not present a problem for creating the
% 'climo' vector later.
% 'teststart' value --> input vector time-of-day -->
% --> 'climo_mx30' time-of-day --> 'climo_mx30 value'

testend = teststart + testlength-1
% Specifies time step at which to stop testing.
% Must be less than length(transfer)-99 in order to avoid trying to compute
% 'mx30' values from after the period covered by the database.

fcstperiods = [1;2;3;4;5;6;7;8;9;10;11;12;13;14;15;16]; fp = fcstperiods;
% Specifies which half-hour periods to forecast for.

% numfcsts = length(fp);

```

```

row = 1;

pers = mx30(teststart-9:testend-9);
% Creates persistence vector for comparison with verification.

Ri = con2seq([smtx30(tstst-d-6:tstst-7); smpk(tstst-d:tstst-1); smdelta2(tstst-d:tstst-1);
    smdir(tstst-d:tstst-1); smtime(tstst-d:tstst-1); smdirdev(tstst-d:tstst-1)]);

R = con2seq([smtx30(tstst-6:testend-6); smpk(tstst:testend); smdelta2(tstst:testend);
    smdir(tstst:testend); smtime(tstst:testend); smdirdev(tstst:testend)]);

Y = sim(net20n,R,Ri); y = seq2con(Y);

for s = 1:16
    random = gamrnd(4.9308,2.5568,1,testlength);
    verify{s} = mx30(tstst+6*(s-1):testend+6*(s-1));
    climo(s,1:testlength) = climo_mx30(climoseed(1)+6*s,2);
    % Creates verification and climatology vectors for comparison with forecasts and persistence.
    fcst{s} = y{1}(s,:);
    rep_320_99025_35(row,1) = 20.99025;
    rep_320_99025_35(row,2) = s*.5;
    rep_320_99025_35(row,3) = std(abs(fcst{s}-verify{s}))/sqrt(testlength);
    rep_320_99025_35(row,4) = mae(fcst{s}-verify{fp(s)});
    rep_320_99025_35(row,5) = mae(pers-verify{fp(s)});
    rep_320_99025_35(row,6) = mae(climo(s,:)-verify{fp(s)});
    rep_320_99025_35(row,7) = mae(random-verify{fp(s)});
    rep_320_99025_35(row,8) = mse(fcst{s}-verify{fp(s)});
    rep_320_99025_35(row,9) = mse(pers-verify{fp(s)});
    rep_320_99025_35(row,10) = mse(climo(s,:)-verify{fp(s)});
    rep_320_99025_35(row,11) = mse(random-verify{fp(s)});
    rep_320_99025_35(row,12) = max(fcst{s}-verify{fp(s)});
    rep_320_99025_35(row,13) = max(pers-verify{fp(s)});
    rep_320_99025_35(row,14) = max(climo(s,:)-verify{fp(s)});
    rep_320_99025_35(row,15) = max(random-verify{fp(s)});
    [fm,fb,rep_320_99025_35(row,16)] = postreg(fcst{s},verify{fp(s)});
    [pm,pb,rep_320_99025_35(row,17)] = postreg(pers,verify{fp(s)});
    [rm,rb,rep_320_99025_35(row,18)] = postreg(random,verify{fp(s)});
    pictures;

    row = row+1;
end;
printmat(rep_320_99025_35,'nil',int2str(1:row-1), ...
    'period vt stdmae fcstmae persmae climomae randommae fcstmse persmse climomse
    randommse fcstmaxerr persmaxerr climomaxerr randommaxerr fcstr persr randomr')
save test320rep99025_35 rep_320_99025_35 -ascii

```

% errsubplots.m Capt Kenneth P. Cloys 8 Jan 00

% Forecasts are generated for each period in data subsets 2 and 3. Proxy error bars are
% determined from MAEs previously computed during program 'nnctest.m' and are added to plots
% of forecasts.

% Verification plots are overlayed to see if the forecasts and Error Bars bound the observations.

meanMAE = rep_320_99025_35(:,4); stdMAE = rep_320_99025_35(:,3);

numtests = 32;

% Specifies number of random start times for which to test NN forecast and error bars against
% observed 30-minute maximum peak winds. Must be a multiple of 8.

for g = 1:numtests/8

for c = 1:8

teststart = 1150+unidrnd(length(transfer)-1255); tstst = teststart;

% Specifies random time step at which to start testing the net on new inputs.

% If neither delta is used, 'teststart' must be at least d+1;

% if only d1 used, at least d+2; if delta2 used, at least d+3.

clear verify;

for i = 1:16

verify(i) = mx30(tstst+6*(i-1));

end; % Creates verification vector for comparison with network forecasts.

Ri = con2seq([smtx30(tstst-d-6:tstst-7); smpk(tstst-d:tstst-1); smdelta2(tstst-d:tstst-1);
smdir(tstst-d:tstst-1); smtime(tstst-d:tstst-1); smdirdev(tstst-d:tstst-1)]);

R = con2seq([smtx30(tstst-6); smpk(tstst); smdelta2(tstst); smdir(tstst); ...
smtime(tstst); smdirdev(tstst)]);

Y = sim(net20n,R,Ri); y = seq2con(Y);

subplot(4,2,c);

plot(.5:.5:8,y{1},'k. '); hold on;

plot(.5:.5:8,y{1} + meanMAE + 2*stdMAE,'r+')

plot(.5:.5:8,y{1} - meanMAE - 2*stdMAE,'r+')

plot(.5:.5:8,verify,'g')

axis tight; %ylabel('kts'); xlabel('Forecast Period (half-hr. increments)')

hold off;

end;

print ('-dmfile','[errplot320_99025_35_' int2str(g)]')

print ('-deps','-tiff','[errplot320_99025_35_' int2str(g)]')

end;

Appendix D: Performance Tables

This appendix contains the performance tables not shown in the text. Values in Original Method tables are averages computed over 250 forecasts; values in Variation tables are averages computed over 100 forecasts.

Table D.1. Results from 5-13 December 1995 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	4.08	0.83	6.84	6.28	17.36	1.11	47.62	61.73
1.0	4.28	0.90	6.79	5.64	19.00	1.54	46.80	54.74
1.5	4.41	1.16	6.87	6.35	20.22	2.14	47.91	72.43
2.0	4.69	1.42	6.56	5.86	22.88	2.87	43.85	65.23
2.5	4.86	1.28	6.29	6.73	24.52	2.90	40.38	91.64
3.0	4.83	1.12	5.76	5.55	24.31	2.39	33.98	48.67
3.5	4.61	1.19	5.29	5.44	22.06	2.00	28.62	51.98
4.0	4.46	1.06	4.93	5.54	20.61	1.79	25.03	53.29
4.5	4.27	1.23	4.85	5.78	19.23	2.16	24.53	60.13
5.0	4.08	1.26	4.53	6.28	17.78	2.21	21.64	62.78
5.5	3.75	1.25	4.65	6.68	15.62	2.33	22.82	78.57
6.0	3.41	1.10	4.60	5.67	13.67	1.93	22.38	55.96
6.5	3.39	1.10	4.47	5.18	13.29	1.67	21.29	49.07
7.0	3.28	1.01	4.36	5.49	12.23	1.48	20.17	58.38
7.5	3.47	1.19	4.18	5.34	13.10	2.10	18.69	49.79
8.0	3.67	1.33	4.09	5.33	14.49	2.55	17.93	45.77
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	6.08	2.00	9.04	20.38				
1.0	6.31	2.00	8.94	23.96				
1.5	6.49	2.90	8.94	27.81				
2.0	6.69	3.80	8.57	29.12				
2.5	6.94	3.90	8.30	36.52				
3.0	8.12	4.80	7.86	18.18				
3.5	7.26	3.90	6.68	22.78				
4.0	6.20	2.90	6.49	25.57				
4.5	6.08	2.00	6.55	28.42				
5.0	5.91	2.90	6.32	19.99				
5.5	5.87	2.00	6.51	45.62				
6.0	5.72	2.90	6.51	23.65				
6.5	5.60	2.90	6.43	20.68				
7.0	5.51	1.90	6.43	31.92				
7.5	5.52	1.90	6.31	18.10				
8.0	5.67	2.90	6.23	16.84				

Table D.2. Results from 5-11 January 1998 (Original Method)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	9.14	1.71	9.38	11.53	89.27	3.90	90.78	156.15
1.0	8.78	1.87	9.37	11.89	83.94	5.86	90.03	166.27
1.5	8.99	1.58	9.53	11.66	88.28	5.33	93.02	161.40
2.0	9.10	1.81	9.55	11.70	87.93	5.15	93.44	160.10
2.5	8.51	2.05	9.63	11.84	76.10	5.47	95.19	166.45
3.0	8.76	2.17	10.00	12.22	79.82	7.79	102.22	178.49
3.5	8.64	2.34	9.99	11.98	77.58	9.12	102.02	174.14
4.0	9.10	2.46	9.96	11.07	85.45	9.46	101.27	147.76
4.5	9.49	2.27	10.03	12.01	92.33	7.38	102.15	167.60
5.0	9.88	2.22	10.23	11.23	99.87	6.46	106.18	154.26
5.5	9.54	2.35	10.45	11.43	93.06	7.54	110.52	158.41
6.0	9.71	2.46	10.68	11.28	96.91	8.86	115.58	155.21
6.5	9.05	2.54	10.58	10.92	85.09	8.70	113.60	147.63
7.0	9.44	2.38	10.51	10.18	91.64	7.74	111.88	129.41
7.5	9.47	2.11	10.63	10.86	91.69	6.87	114.18	141.58
8.0	9.52	1.96	10.42	10.50	93.17	5.95	109.85	132.63
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	-4.56	3.10	-6.39	6.42				
1.0	-3.83	4.10	-6.25	10.08				
1.5	-2.60	4.10	-6.37	8.05				
2.0	-3.20	3.10	-6.42	10.05				
2.5	-3.28	2.90	-6.54	6.64				
3.0	-3.97	4.10	-6.86	9.98				
3.5	-3.73	4.10	-6.96	3.44				
4.0	-5.40	4.10	-7.04	12.05				
4.5	-5.73	4.10	-7.33	3.51				
5.0	-6.54	4.10	-7.71	13.34				
5.5	-7.16	5.00	-8.04	8.17				
6.0	-5.87	6.00	-8.40	13.68				
6.5	-4.76	6.00	-8.45	4.99				
7.0	-5.25	4.10	-8.45	10.32				
7.5	-6.70	5.00	-8.68	7.54				
8.0	-6.12	6.00	-8.49	4.15				

Table D.3. Results from 24 January – 1 February 1996 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	11.00	3.13	13.93	14.10	144.22	18.40	246.65	249.23
1.0	10.63	4.44	14.70	15.60	128.18	40.06	261.65	305.43
1.5	9.05	5.44	15.53	15.76	91.35	60.03	273.21	295.47
2.0	9.00	6.02	16.43	16.74	90.57	76.24	289.67	321.15
2.5	10.78	6.32	17.23	17.76	124.88	86.87	304.24	351.06
3.0	13.04	7.10	17.60	16.97	180.55	99.15	313.60	317.13
3.5	15.37	7.73	17.67	17.63	245.29	105.78	315.74	341.54
4.0	19.50	8.12	17.50	18.48	391.30	109.24	310.91	370.28
4.5	21.54	8.43	17.22	16.55	478.58	112.65	302.11	307.36
5.0	18.96	8.62	16.93	16.65	371.20	114.30	293.36	317.34
5.5	16.66	8.84	16.29	16.51	291.13	117.51	273.83	300.86
6.0	15.00	9.13	15.64	14.33	241.26	120.39	254.94	248.16
6.5	13.01	9.37	15.15	15.28	185.94	120.65	241.06	268.49
7.0	13.06	9.47	14.62	13.45	191.35	116.76	224.82	212.46
7.5	14.11	9.56	14.25	14.02	223.15	112.67	213.38	229.81
8.0	13.94	9.39	13.89	13.89	220.80	107.82	201.36	223.34
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	7.35	7.00	1.21	14.33				
1.0	7.35	9.00	1.24	7.28				
1.5	8.72	10.90	1.41	25.91				
2.0	7.66	10.90	1.32	8.96				
2.5	-3.80	5.10	-8.57	-1.37				
3.0	-6.16	6.10	-10.52	5.89				
3.5	-8.23	6.10	-13.72	-0.28				
4.0	-12.52	6.10	-13.76	-2.72				
4.5	-11.83	8.20	-11.66	2.29				
5.0	-10.98	9.20	-10.86	4.30				
5.5	-9.08	10.10	-9.90	2.73				
6.0	-6.26	11.10	-8.82	12.48				
6.5	-4.19	10.10	-8.82	5.11				
7.0	-5.44	11.10	-8.85	11.92				
7.5	-5.06	10.10	-8.87	2.74				
8.0	-4.94	11.10	-9.01	9.46				

Table D.4. Results from 14-22 December 1996 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	5.19	1.48	1.48	5.19	44.54	3.54	3.11	41.82
1.0	6.12	1.69	1.57	5.34	61.51	4.33	3.53	41.29
1.5	6.42	1.40	1.81	4.40	65.92	3.18	4.51	27.19
2.0	5.62	1.48	1.71	4.51	50.43	3.53	3.77	30.29
2.5	4.29	1.74	1.78	4.42	31.50	4.67	4.10	29.91
3.0	3.32	1.76	1.61	4.98	19.59	5.25	3.46	41.22
3.5	3.04	2.09	1.59	5.59	15.51	6.60	3.36	47.36
4.0	2.63	2.35	1.47	5.65	10.27	7.65	2.93	47.34
4.5	2.30	2.24	1.35	4.71	6.61	6.64	2.61	34.59
5.0	2.12	1.95	1.38	5.31	5.98	5.05	2.65	42.59
5.5	1.93	1.74	1.44	4.68	5.62	4.68	2.67	31.63
6.0	2.22	1.64	1.43	4.46	7.95	5.15	2.63	29.80
6.5	2.87	1.53	1.40	5.16	12.50	4.09	2.56	38.28
7.0	2.89	1.49	1.57	5.14	12.66	3.23	3.31	44.27
7.5	2.35	1.78	1.71	4.86	8.53	4.37	3.94	36.05
8.0	1.29	1.76	1.61	4.08	2.45	4.53	3.51	28.26
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	13.46	3.80	4.43	19.41				
1.0	15.86	4.80	4.44	20.40				
1.5	16.60	3.80	4.80	16.99				
2.0	14.30	4.80	3.58	17.75				
2.5	11.01	4.80	3.65	16.90				
3.0	8.91	4.80	3.50	20.56				
3.5	8.38	4.80	3.47	20.23				
4.0	7.39	4.80	3.22	19.24				
4.5	5.20	3.80	2.96	15.02				
5.0	4.46	2.90	2.94	18.06				
5.5	5.13	2.90	2.74	13.27				
6.0	5.54	1.90	2.46	16.04				
6.5	6.72	1.90	2.12	16.68				
7.0	6.68	2.90	1.61	28.26				
7.5	6.18	3.80	1.37	21.46				
8.0	3.26	3.80	1.45	15.81				

Table D.5. Results from 6-21 January 1997 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	7.22	1.66	2.17	5.53	62.32	4.14	7.12	48.98
1.0	8.30	2.00	2.68	4.78	95.65	6.35	10.43	39.29
1.5	9.99	2.24	3.15	5.87	143.47	8.06	14.01	50.29
2.0	10.61	2.45	3.71	5.19	169.26	8.66	18.35	41.12
2.5	10.00	2.53	4.22	5.36	148.09	9.38	22.43	53.78
3.0	11.17	2.72	4.42	4.90	178.85	10.33	24.32	37.30
3.5	10.63	3.06	5.10	5.28	154.95	12.09	30.15	49.09
4.0	8.85	3.54	5.29	5.80	112.40	15.28	31.32	55.51
4.5	8.78	3.65	5.43	5.04	108.97	16.50	32.54	45.25
5.0	9.31	3.68	5.32	4.49	124.81	16.39	31.20	35.13
5.5	8.37	3.54	5.40	5.49	93.81	16.09	31.94	53.85
6.0	8.78	3.79	5.16	5.29	82.11	18.42	29.38	49.58
6.5	9.91	3.82	4.96	4.61	113.39	20.89	27.27	37.39
7.0	11.52	3.85	5.06	4.16	170.32	23.17	27.81	32.31
7.5	14.70	4.03	4.98	5.47	263.28	25.70	26.59	49.53
8.0	15.13	3.89	4.65	4.71	303.23	25.20	23.48	44.91
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	13.17	4.10	6.67	28.19				
1.0	17.99	5.10	7.28	19.65				
1.5	20.29	6.10	7.74	17.58				
2.0	22.87	6.10	8.08	19.53				
2.5	20.16	7.00	8.33	34.74				
3.0	23.56	6.00	8.34	16.27				
3.5	20.83	7.00	8.70	21.56				
4.0	18.26	7.00	8.68	22.08				
4.5	19.54	7.00	8.75	23.02				
5.0	22.00	8.20	8.60	18.30				
5.5	19.19	8.00	8.57	27.60				
6.0	13.54	7.90	8.32	25.74				
6.5	16.31	8.90	8.06	17.02				
7.0	19.24	9.90	8.04	21.59				
7.5	21.61	10.90	7.84	19.90				
8.0	26.58	10.90	7.56	30.83				

Table D.6. Results from 25 November - 2 December 1997 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	5.69	0.64	6.95	6.52	40.76	0.88	49.59	64.95
1.0	5.88	1.08	6.74	6.36	43.91	1.92	46.76	66.25
1.5	7.31	1.55	6.35	5.72	67.03	3.43	42.24	57.39
2.0	7.33	1.92	5.89	6.23	67.22	4.76	37.06	62.86
2.5	6.49	2.00	5.34	6.00	56.72	5.52	31.04	63.04
3.0	6.68	2.11	5.22	5.51	56.55	6.47	30.03	52.80
3.5	6.94	2.19	5.37	6.91	62.47	7.51	31.75	81.00
4.0	5.89	2.26	5.20	6.71	48.17	8.12	30.08	84.60
4.5	5.83	2.13	5.12	6.47	41.00	7.59	29.24	71.16
5.0	5.69	1.95	5.18	5.76	40.52	6.80	29.73	49.11
5.5	5.00	1.92	4.98	6.15	35.34	6.06	27.57	64.02
6.0	5.00	1.81	4.88	5.39	32.98	5.21	26.45	50.31
6.5	5.01	1.77	4.82	5.60	33.33	4.68	25.87	49.69
7.0	4.91	1.81	4.84	6.38	34.06	4.77	26.38	67.08
7.5	4.72	1.82	4.92	6.33	32.67	4.51	27.44	71.67
8.0	4.95	1.63	4.96	6.26	33.06	3.35	27.91	60.74
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	9.52	1.90	8.94	25.81				
1.0	10.65	2.90	8.74	24.14				
1.5	13.82	3.10	8.46	28.91				
2.0	12.87	4.10	8.12	28.19				
2.5	13.58	4.10	7.61	26.26				
3.0	11.38	4.10	7.37	22.10				
3.5	12.32	4.10	7.45	41.22				
4.0	16.23	5.10	7.21	35.51				
4.5	14.79	5.10	7.24	28.30				
5.0	14.89	5.10	7.41	17.86				
5.5	15.51	5.10	7.32	21.62				
6.0	13.46	6.00	7.33	22.03				
6.5	10.56	4.10	7.28	22.75				
7.0	10.44	4.10	7.18	25.57				
7.5	10.72	4.10	7.14	23.94				
8.0	9.98	4.10	7.14	30.07				

Table D.7. Results from 5-11 January 1998 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	7.50	2.31	4.42	5.34	73.55	8.60	26.56	48.58
1.0	9.92	3.12	4.88	5.70	128.36	14.24	32.89	55.98
1.5	10.75	3.44	5.09	6.19	150.15	17.70	35.13	62.08
2.0	11.26	3.85	5.09	6.46	148.02	23.55	34.33	70.30
2.5	6.24	4.01	4.65	5.19	64.30	24.80	29.46	47.97
3.0	7.58	3.96	4.44	5.63	66.68	24.69	27.33	58.65
3.5	12.38	3.37	4.45	5.79	195.15	19.32	27.48	56.65
4.0	5.58	3.22	4.22	5.86	43.28	17.58	25.23	59.91
4.5	4.22	2.92	4.31	5.39	25.28	15.68	25.97	51.05
5.0	5.69	3.02	4.54	5.67	41.15	13.70	27.96	55.04
5.5	5.60	2.94	4.50	5.91	38.04	13.94	27.37	66.29
6.0	4.19	3.26	4.75	5.88	23.07	16.27	29.13	55.13
6.5	4.45	3.65	4.86	6.14	26.78	21.90	29.53	64.01
7.0	5.54	3.79	4.90	5.52	43.09	27.43	29.19	55.18
7.5	6.40	3.71	4.82	5.86	54.00	30.63	28.49	55.73
8.0	6.64	3.75	4.83	7.04	62.02	32.92	28.56	86.04
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	17.87	8.90	14.04	23.91				
1.0	17.73	8.90	13.84	24.11				
1.5	21.43	8.90	13.56	20.64				
2.0	21.66	13.00	13.22	26.14				
2.5	19.51	11.10	12.71	19.91				
3.0	16.39	11.10	12.47	27.56				
3.5	25.97	9.90	12.55	22.31				
4.0	16.28	9.90	12.31	29.13				
4.5	10.59	8.90	12.34	28.89				
5.0	13.33	8.00	12.51	21.29				
5.5	14.91	8.90	12.42	28.73				
6.0	11.40	8.90	12.43	19.06				
6.5	8.07	12.10	12.38	21.69				
7.0	10.89	15.00	12.28	21.48				
7.5	9.48	15.00	12.24	18.57				
8.0	5.41	15.90	12.24	31.95				

Table D.8. Results from 4-18 March 1998 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	5.39	1.51	12.01	11.96	38.44	3.64	158.15	174.38
1.0	4.73	1.89	12.46	12.99	31.22	5.56	169.71	196.87
1.5	4.32	2.46	13.03	12.06	27.47	8.41	182.73	181.99
2.0	4.65	2.90	13.36	12.03	30.70	12.82	189.69	175.11
2.5	5.18	3.39	13.60	13.36	37.50	16.01	194.63	214.61
3.0	6.08	3.71	13.97	14.17	47.50	20.73	203.26	237.19
3.5	7.94	4.05	14.24	14.93	70.94	24.78	209.65	251.13
4.0	9.33	4.34	14.39	14.74	93.29	27.68	212.77	251.64
4.5	8.91	4.83	13.98	15.65	82.88	32.48	199.58	280.10
5.0	7.27	5.20	13.87	15.41	56.03	36.02	195.65	268.69
5.5	6.64	5.63	13.44	14.89	47.14	40.04	183.64	253.24
6.0	6.38	5.79	13.45	16.28	43.47	42.22	183.52	289.47
6.5	6.51	5.75	13.34	14.78	44.61	43.03	180.39	253.89
7.0	7.03	5.59	13.08	15.81	52.07	41.37	173.60	276.03
7.5	7.48	5.26	13.08	15.39	59.70	41.25	173.63	271.57
8.0	7.35	5.06	12.99	15.55	57.78	38.36	171.24	267.52
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	0.84	4.80	-5.31	6.33				
1.0	2.62	3.90	-5.21	4.41				
1.5	1.42	3.00	-7.45	8.37				
2.0	0.72	3.90	-8.27	9.58				
2.5	1.14	3.90	-8.10	13.95				
3.0	-0.22	3.00	-7.92	4.39				
3.5	-2.11	3.00	-7.65	9.81				
4.0	-3.70	1.90	-9.24	3.52				
4.5	-4.93	2.90	-9.42	1.00				
5.0	-2.47	3.90	-9.16	7.23				
5.5	-3.73	4.80	-9.65	8.81				
6.0	-3.50	3.00	-10.77	8.22				
6.5	-3.37	3.90	-10.62	15.52				
7.0	-2.56	2.00	-10.40	4.11				
7.5	-2.70	2.00	-10.35	1.05				
8.0	-2.45	2.90	-10.35	11.06				

Table D.9. Results from 8-17 November 1998 (Variation)

Forecast Valid Time	Neural Net MAE (kts)	Persist- ence MAE (kts)	Climo MAE (kts)	Random MAE (kts)	Neural Net MSE (kts ²)	Persist- ence MSE (kts ²)	Climo MSE (kts ²)	Random MSE (kts ²)
0.5	4.55	1.27	6.41	6.81	29.22	2.73	45.75	79.54
1.0	5.06	1.99	6.68	6.49	35.84	5.44	50.32	82.71
1.5	5.00	2.49	7.17	6.60	36.07	7.55	58.08	71.47
2.0	5.11	2.74	7.63	6.30	35.28	9.85	65.12	69.09
2.5	5.50	2.95	7.93	6.80	36.13	12.48	69.64	80.58
3.0	5.89	3.05	8.28	7.06	38.44	13.41	74.32	81.53
3.5	6.04	3.20	8.46	6.85	39.41	14.24	76.40	75.54
4.0	6.20	3.30	8.82	8.13	40.02	14.27	81.35	96.22
4.5	6.05	3.42	8.97	7.88	38.14	15.63	83.61	99.39
5.0	5.79	3.62	8.88	8.03	35.90	17.04	81.39	98.07
5.5	5.34	3.72	8.91	7.50	32.74	18.40	81.63	81.46
6.0	5.10	3.62	8.70	7.88	30.31	18.46	77.63	102.20
6.5	4.93	3.59	8.63	8.07	28.57	17.82	76.10	103.38
7.0	4.96	3.48	8.04	7.76	28.96	17.24	66.69	90.12
7.5	4.87	3.49	7.57	8.54	28.17	16.98	59.85	103.83
8.0	4.81	3.43	7.21	7.34	26.69	16.26	54.79	85.85
Forecast Valid Time	Neural Net Max Error (kts)	Persist- ence Max Error (kts)	Climo Max Error (kts)	Random Max Error (kts)				
0.5	10.45	2.20	11.35	31.72				
1.0	11.65	3.10	11.43	46.52				
1.5	10.55	4.10	11.58	24.65				
2.0	10.30	4.10	11.80	22.49				
2.5	9.51	5.10	11.85	35.72				
3.0	8.97	5.10	11.85	26.48				
3.5	8.96	6.00	11.70	34.58				
4.0	9.28	6.00	11.60	23.89				
4.5	9.14	8.20	11.42	32.25				
5.0	8.77	8.20	11.16	24.15				
5.5	10.11	8.20	11.14	20.36				
6.0	8.81	8.20	10.80	34.03				
6.5	10.01	8.20	10.66	33.32				
7.0	9.37	7.00	10.16	22.56				
7.5	8.35	6.00	9.81	24.85				
8.0	8.12	8.20	9.57	27.12				

Appendix E: 8-hour Forecasts with Reliability Intervals

Included in this appendix are eight notional operational 8-hour forecasts for each of the periods in database Subsets 2 and 3. During network testing, 32 such forecasts were generated for each period, so only a sample for each period is shown here. The plots incorporate the reliability intervals computed for the 100-sample forecasts displayed in Figures 5.2 through 5.17.

Each set of forecasts shown here was generated by a neural network trained only on data from the same period as the forecast. Forecast start times were chosen at random from among the points not used in training the network.

In all figures, the solid line depicts the observed 30-minute maximum wind speed, and the dotted line represents the neural network's forecast for the 30-minute maximum wind speed. The + 's mark the reliability intervals described in Chapter 4.

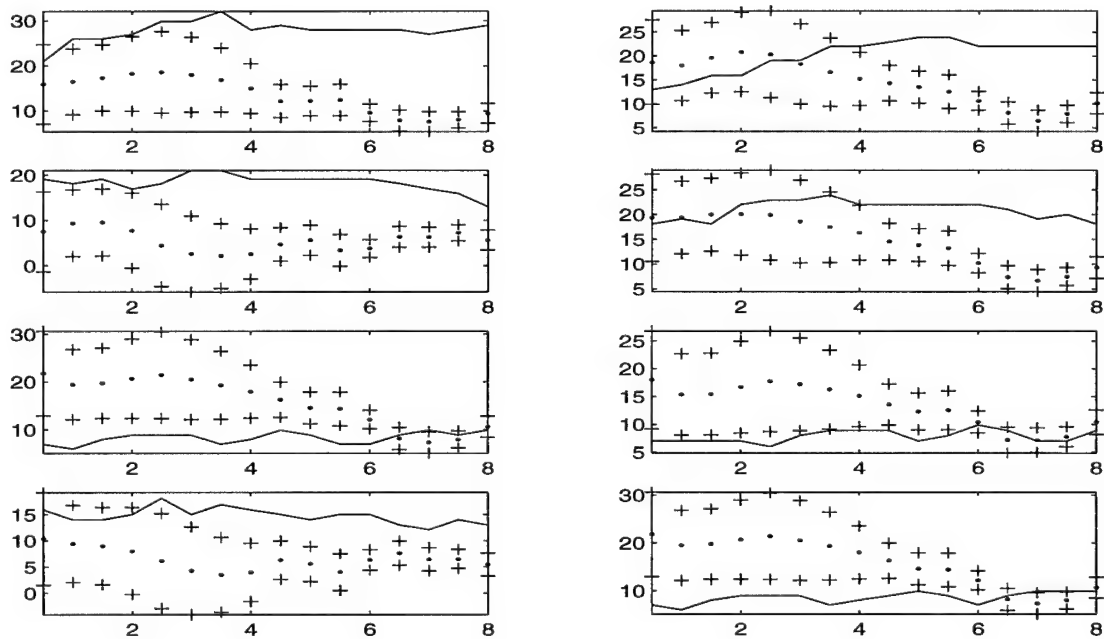


Figure E.1. Forecasts and Reliability Intervals for 5-13 December 1995.

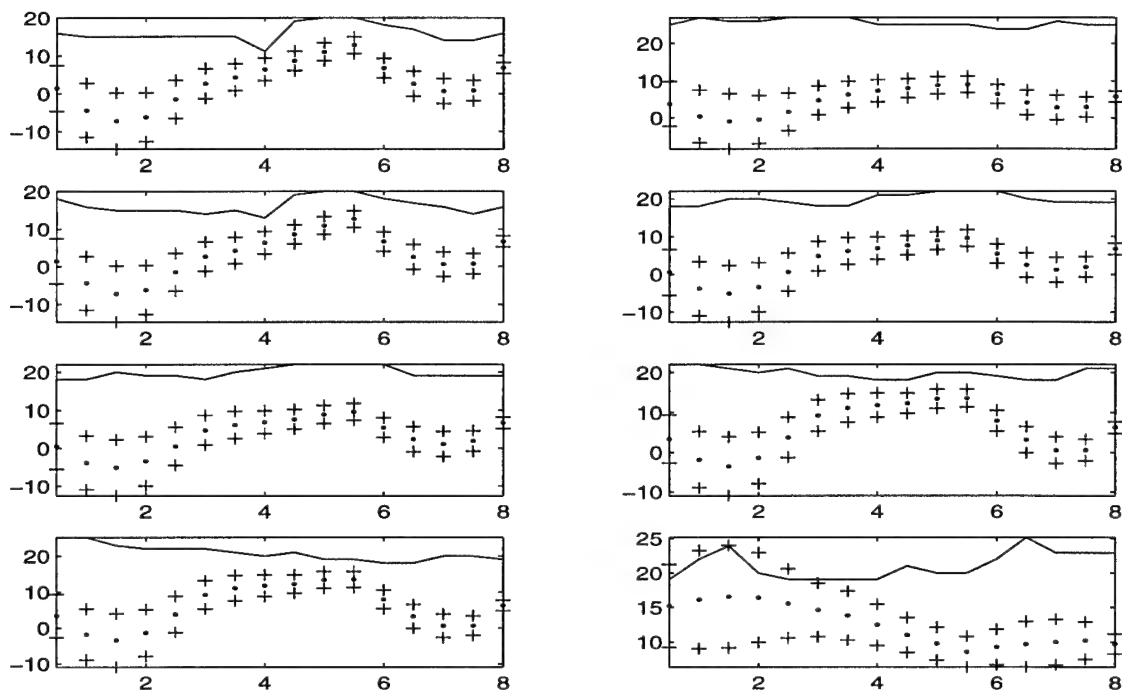


Figure E.2. Forecasts and Reliability Intervals for 14-22 December 1996.

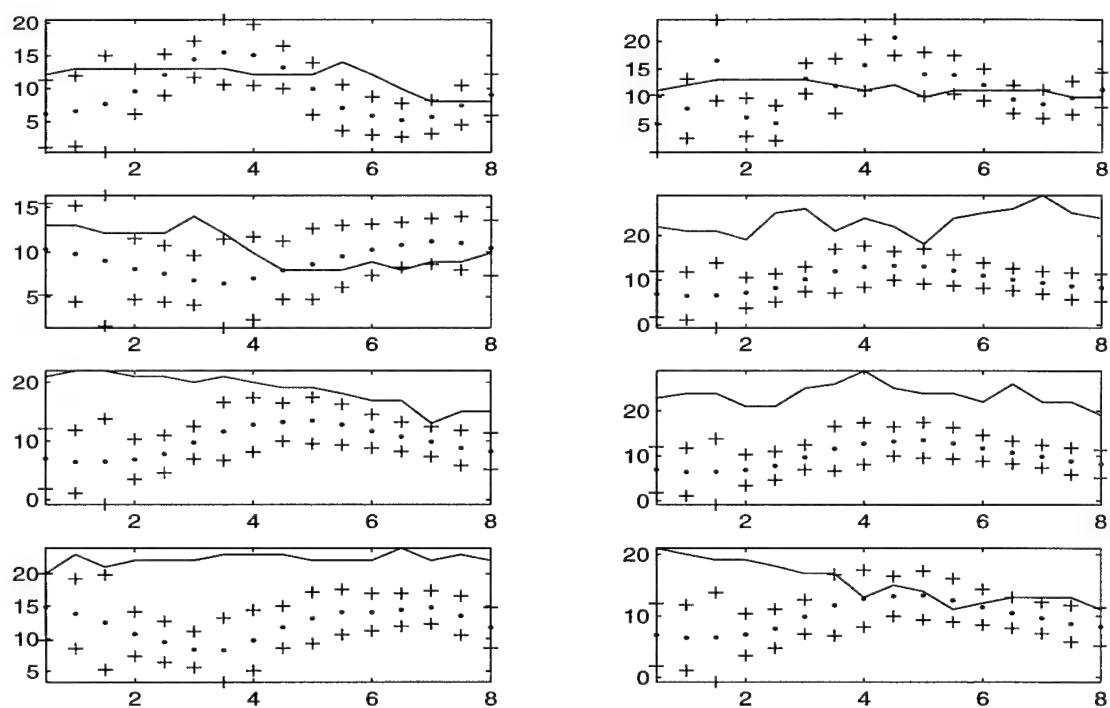


Figure E.3. Forecasts and Reliability Intervals for 23 February – 7 March 1996.

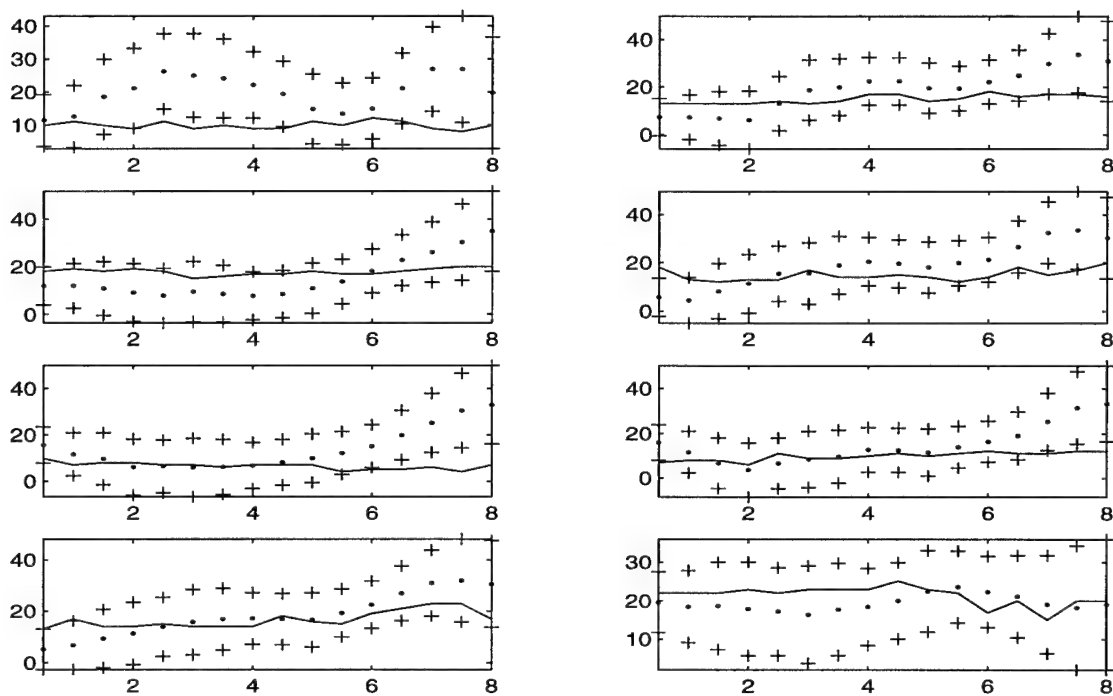


Figure E.4. Forecasts and Reliability Intervals for 6-21 January 1997.

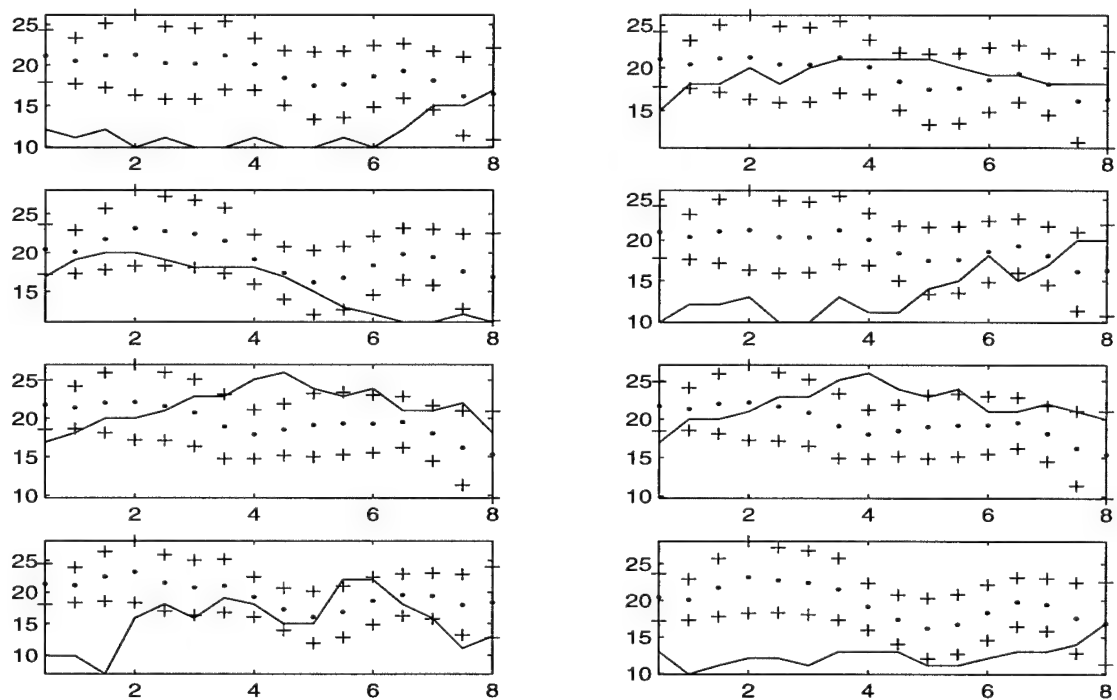


Figure E.5. Forecasts and Reliability Intervals for 24 November – 8 December 1996.

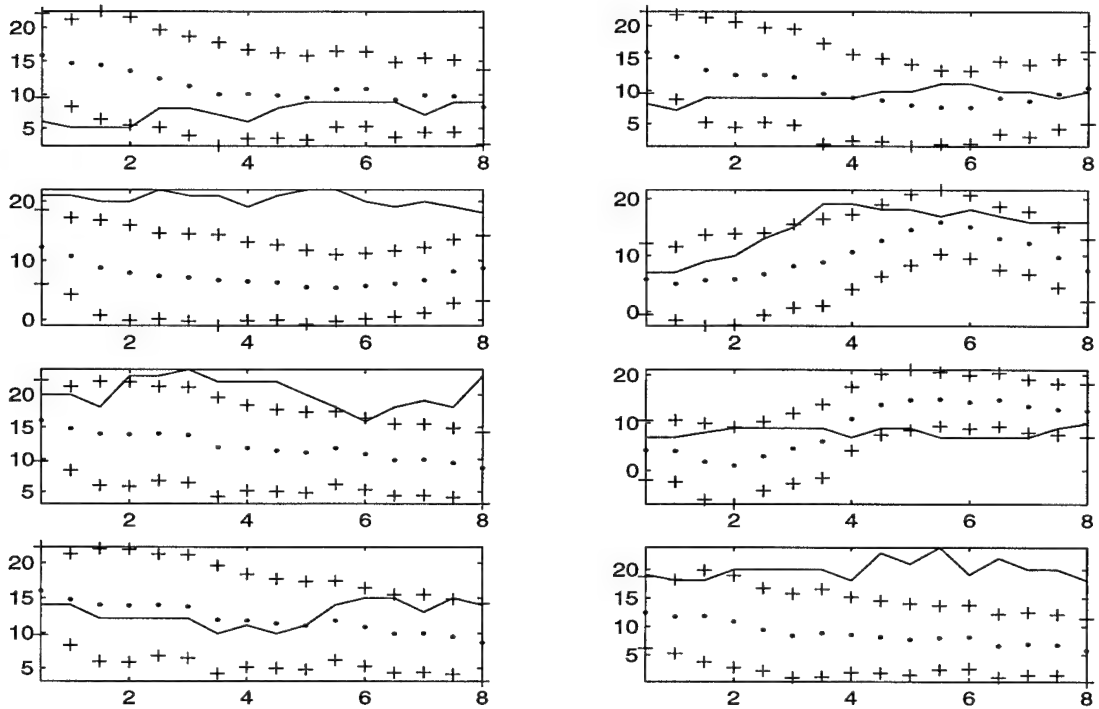


Figure E.6. Forecasts and Reliability Intervals for 25 November – 2 December 1997.

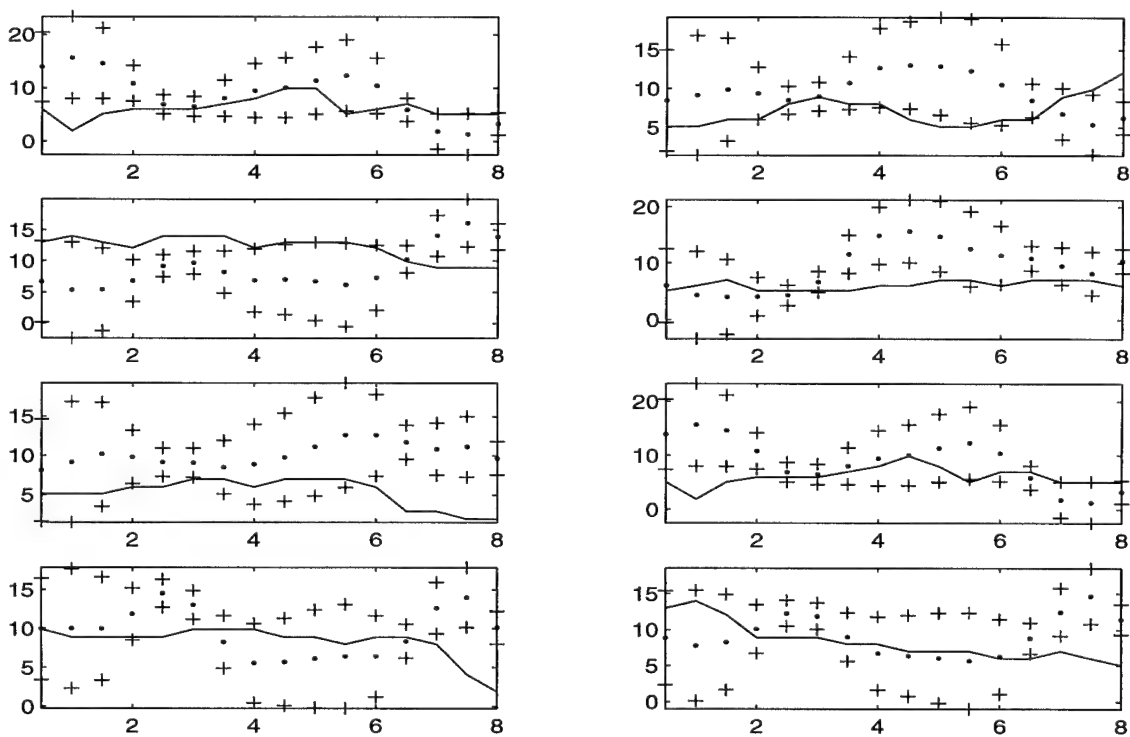


Figure E.7. Forecasts and Reliability Intervals for 29 January – 6 February 1997.

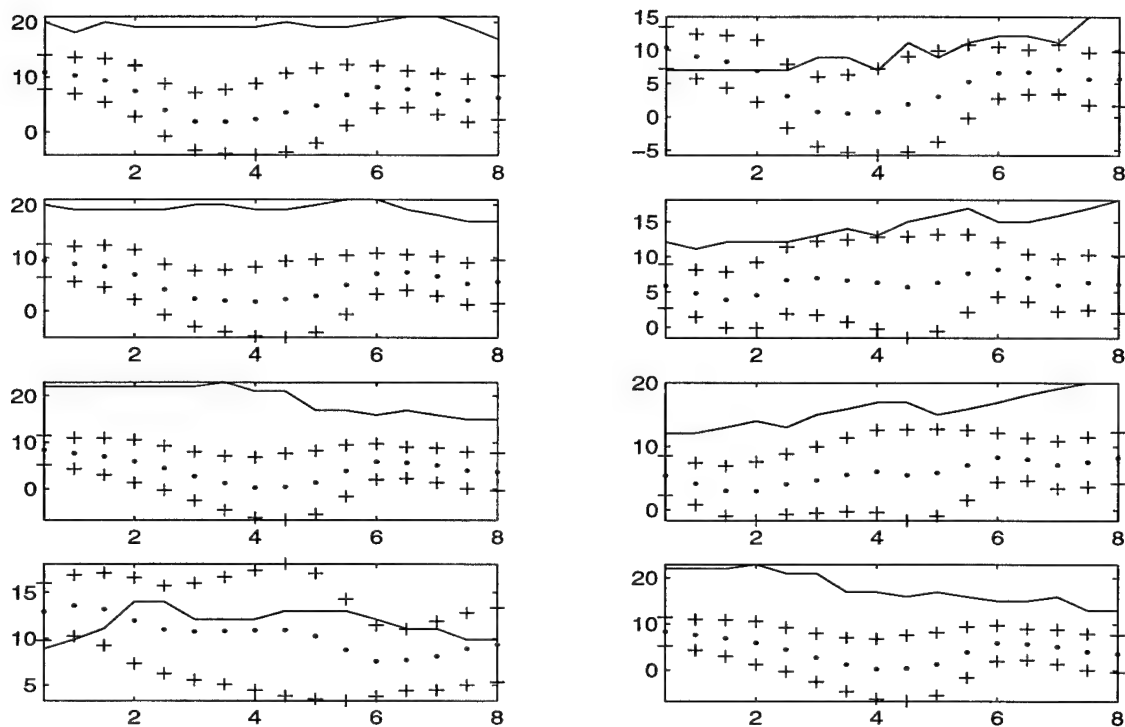


Figure E.8. Forecasts and Reliability Intervals for 1-10 March 1997.

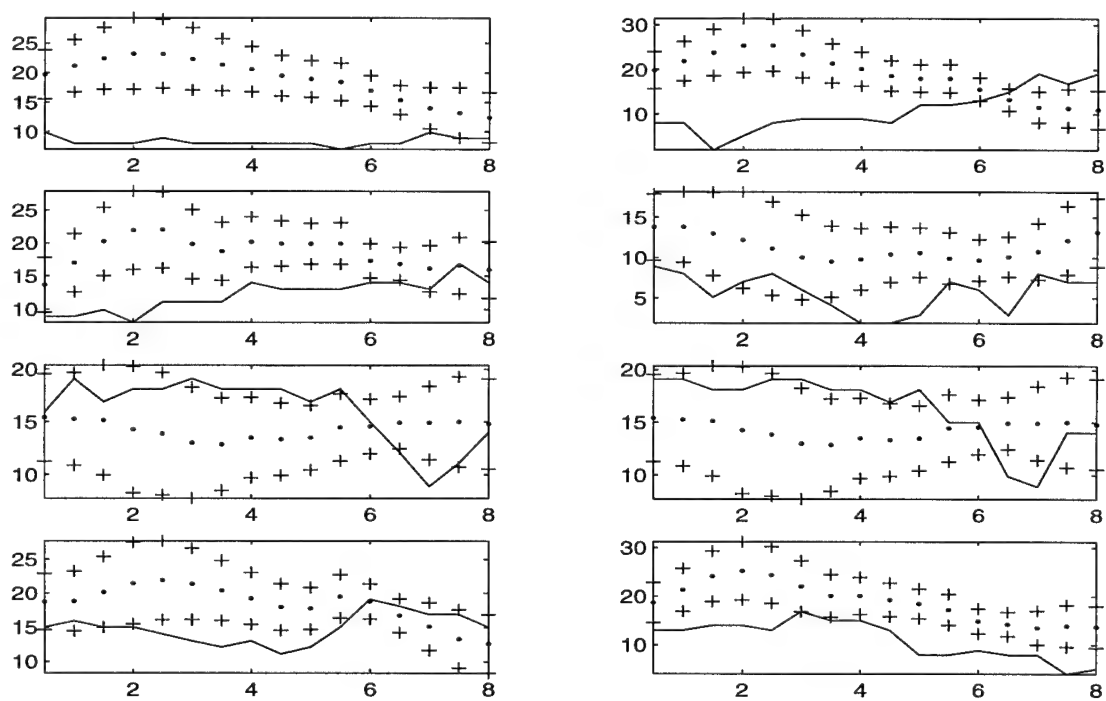


Figure E.9. Forecasts and Reliability Intervals for 2-13 December 1997.

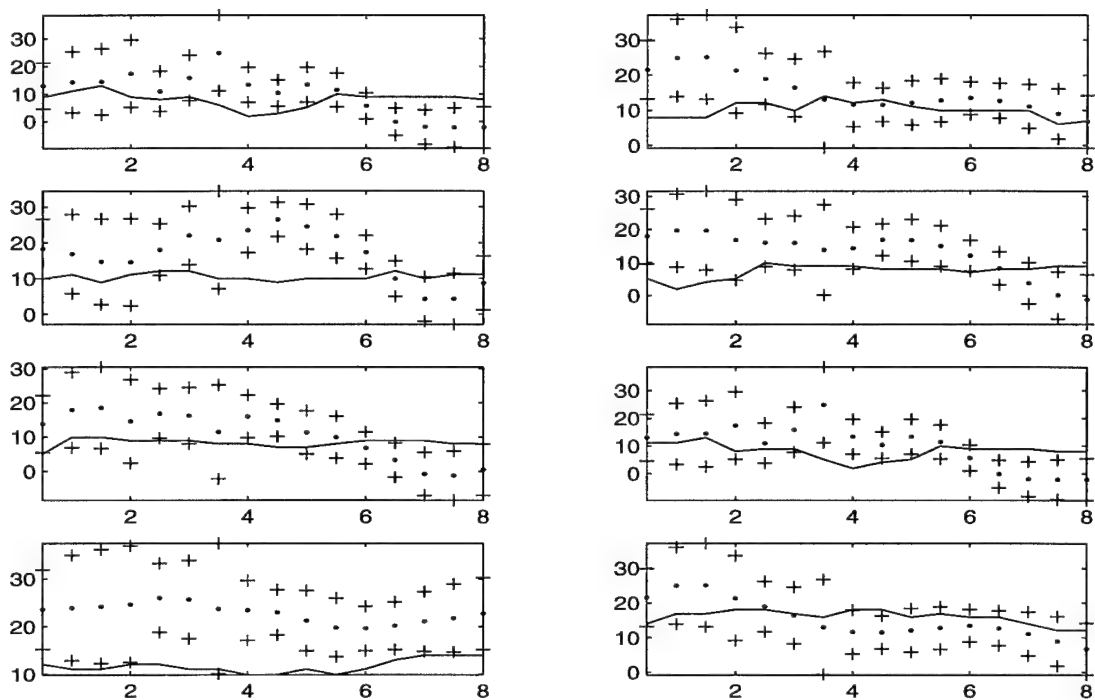


Figure E.10. Forecasts and Reliability Intervals for 5-11 January 1998.

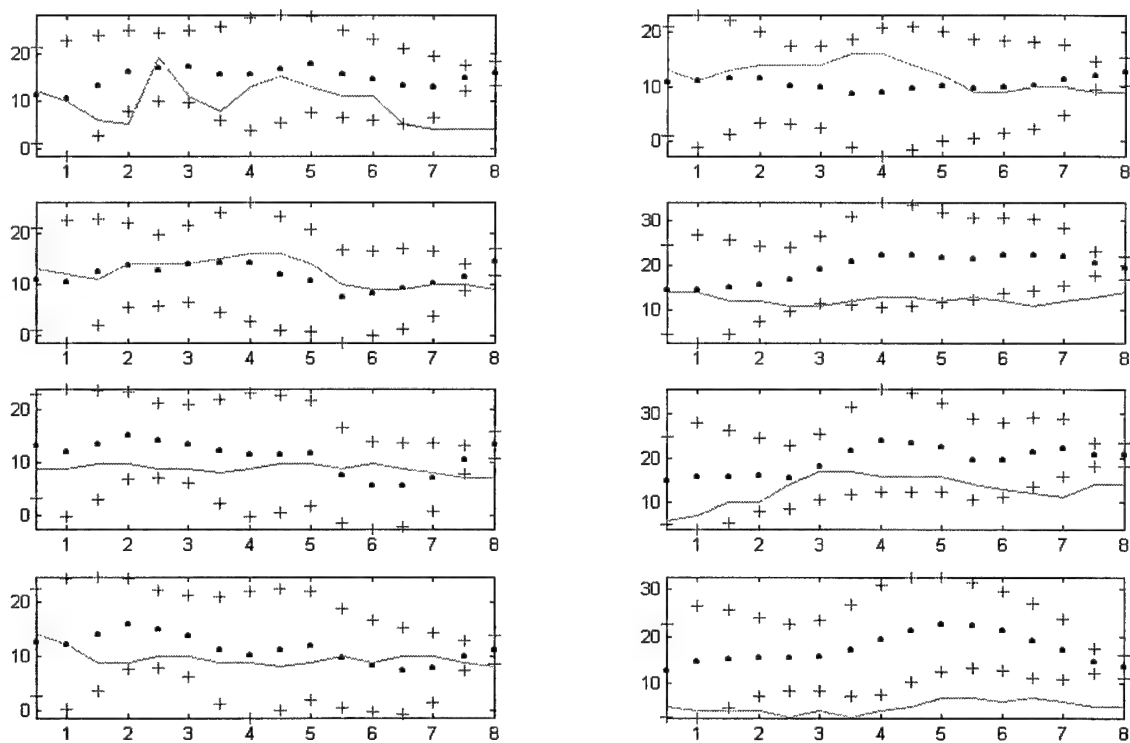


Figure E.11. Forecasts and Reliability Intervals for 14-20 January 1999.

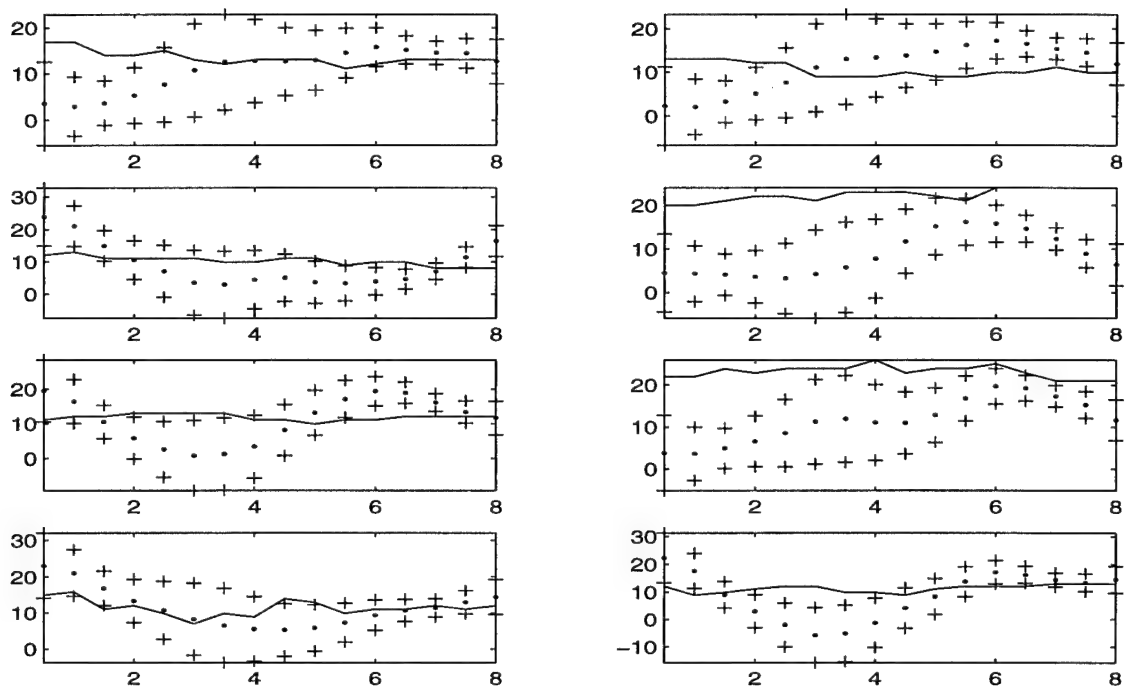


Figure E.12. Forecasts and Reliability Intervals for 21-31 March 1999.

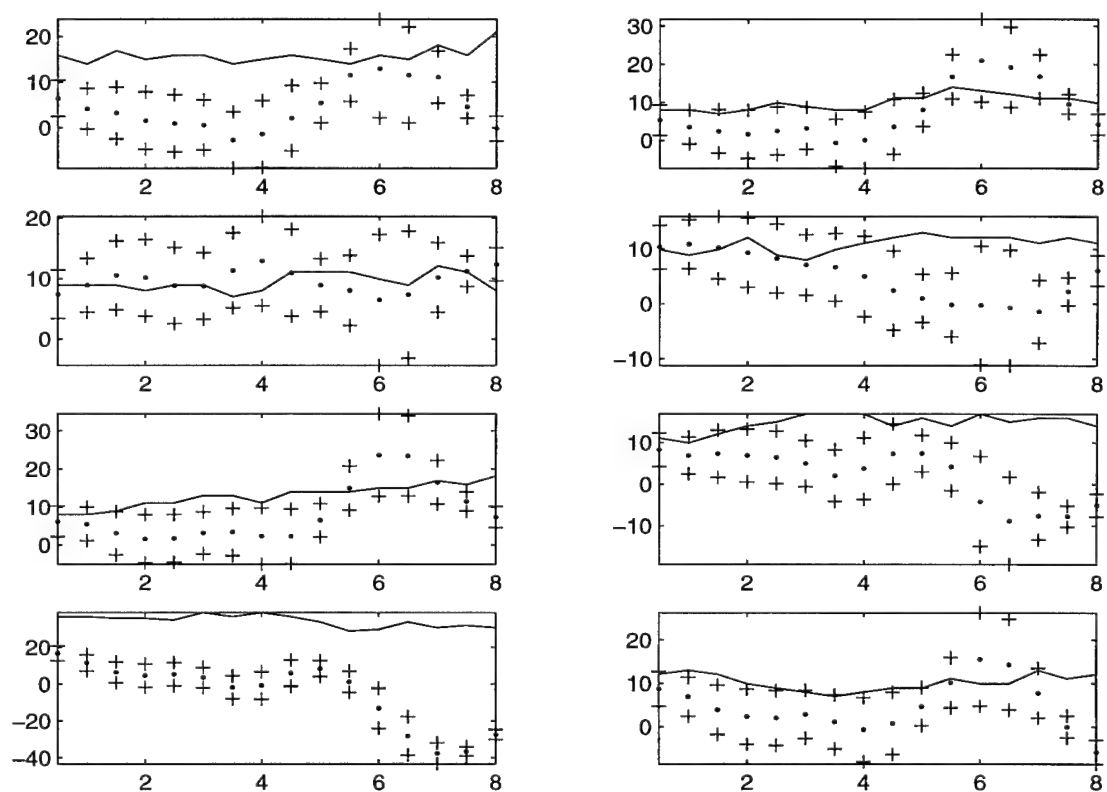


Figure E.13. Forecasts and Reliability Intervals for 25 January – 4 February 1999.

Bibliography

- Dean, J. S., 1994: Subgrouped Real Time Recurrent Learning Neural Networks. M.S. thesis, Air Force Institute of Technology, Wright-Patterson Air Force Base, Dayton, OH, 144 pp.
- Dewdney, A. K., 1997: Yes, We Have No Neutrons. John Wiley & Sons, 180 pp.
- Elsner, J. B., and A. A. Tsonis, 1992: Nonlinear Prediction, Chaos, and Noise. *Bull. Amer. Meteor. Soc.*, **73**, 49-60
- Gainey, J. C., 1993: Predicting Nonlinear Time Series. M.S. thesis, Air Force Institute of Technology, Wright-Patterson Air Force Base, Dayton, OH, 123 pp.
- Hall, Tony, Harold E. Brooks, and Charles A. Dowell, III, 1999: Precipitation Forecasting Using a Neural Network. *Wea. Forecasting*, **14**, 338-345.
- Heim, E. S., 1995: A Neural Network Approach to the Prediction and Confidence Assignment of Nonlinear Time Series Classifications. M.S. thesis, Air Force Institute of Technology, Wright-Patterson Air Force Base, Dayton, OH, 54 pp.
- Khotanzad, Alireza, Reza Afkhami-Rohani, Tsun-Liang Lu, Alireza Abaye, Malcolm Davis, and Dominic J. Maratukulam, 1997: A Neural-Network-Based Electric Load Forecasting System. *IEEE Transactions on Neural Networks*, **8**, 835-845.
- Kuligowski, Robert J., and Ana P. Barros, 1998: Experiments in Short-Term Precipitation Forecasting Using Artificial Neural Networks. *Mon. Wea. Rev.*, **126**, 470-482.
- Lindsey, Randall L., 1991: Function Prediction Using Recurrent Neural Networks. M.S. thesis, Air Force Institute of Technology, Wright-Patterson Air Force Base, Dayton, OH, 110 pp.
- Marzban, Caren and Gregory J. Stumpf, 1996: A Neural Network for Tornado Prediction Based on Doppler Radar-Derived Attributes. *J. Appl. Meteor.*, **35**, 617-626.
- McCann, D. W., 1992: A Neural Net Short-Term Forecast of Significant Thunderstorms. *Wea. Forecasting*, **7**, 525-534.
- NewWave Intelligent Business Systems, NIBS Inc., 31 December 1999: Neural Network Computing. Excerpt from unpublished article, n. pag. <http://sunflower.singnet.com.sg/~midaz/Intronn.htm>.

Park, Young R., Thomas J. Murray, and Chung Chen, 1996: Predicting Sun Spots Using a Layered Perceptron Neural Network. *IEEE Transactions on Neural Networks*, **7**, 501-505.

Roadknight, Chris M., Graham R. Balls, Gina E. Mills, and Dominic Palmer-Brown, 1997: Modeling Complex Environmental Data. *IEEE Transactions on Neural Networks*, **8**, 852-861.

Roeder, W. P., Chief Staff Meteorologist for the 45th Weather Squadron, Patrick Air Force Base, FL, 1999: Personal interview. 13 February 1999.

----- Personal correspondence. 8 December 1999.

Rogers, Steven K., Matthew Kabrisky, Dennis W. Ruck, Gregory L. Tarr, 1990: An Introduction to Biological and Artificial Neural Networks. Air Force Institute of Technology, Wright-Patterson Air Force Base, Dayton, OH, 240 pp.

Saad, Emad W., Danil V. Prokhorov, and Donald C. Wunsch, II, 1998: Comparative Study of Stock Trend Prediction Using Time Delay, Recurrent and Probabilistic Neural Networks. *IEEE Transactions on Neural Networks*, **9**, 1456-1469.

Storch, S. J., 1999: Predicting Launch Pad Winds at the Kennedy Space Center with a Neural Network Model. M.S. thesis, Air Force Institute of Technology, Wright-Patterson Air Force Base, Dayton, OH, 60 pp.

Vita

Captain Kenneth P. Cloys was born on 22 September 1962 in Lexington, Kentucky. He graduated from LaFayette High School in June 1980. He entered undergraduate studies at Florida State University in Tallahassee, Florida, where he graduated with a Bachelor of Science degree in Meteorology in May 1994. He was commissioned through Officer Training School at Maxwell Air Force Base, Montgomery, Alabama.

His first assignment was at Scott Air Force Base, Belleville, Illinois, where he served as Tactical Program Manager for the Air Force Combat Climatology Center. In June 1996, he was assigned to the 49th Fighter Wing, Holloman AFB, New Mexico, where he served as the Weather Flight's Wing Weather Officer.

In August 1998, he entered the Graduate School of Engineering, Air Force Institute of Technology. Upon graduation, he will be assigned to the 28th Operational Weather Squadron at Shaw AFB, South Carolina.

REPORT DOCUMENTATION PAGE			Form Approved OMB No. 074-0188	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503				
1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE March 2000	3. REPORT TYPE AND DATES COVERED Master's Thesis	
4. TITLE AND SUBTITLE A NEURAL NETWORK SOLUTION TO PREDICTING WIND SPEED AT CAPE CANAVERAL'S ATLAS LAUNCH PAD			5. FUNDING NUMBERS	
6. AUTHOR(S) Kenneth P. Cloys, Captain, USAF				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 P Street, Building 640 WPAFB OH 45433-7765			8. PERFORMING ORGANIZATION REPORT NUMBER AFIT/GM/ENP/00M-03	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) 45 WS/SYR Attn: Mr. William P. Roeder 1201 Edward H. White II St., MS 7302 Patrick AFB FL 32925-3238 DSN: 467-8410			10. SPONSORING / MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES Lt Col Michael K. Walters, ENP, DSN: 785-3636, ext. 4681				
12a. DISTRIBUTION / AVAILABILITY STATEMENT APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.			12b. DISTRIBUTION CODE	
ABSTRACT (Maximum 200 Words) <p>This thesis demonstrates the potential for using time-delay neural networks to provide Launch Weather Officers (LWOs) at 45th Weather Squadron (45 WS) with advance warning of wintertime (November-March) peak wind speeds at the Atlas launch pad.</p> <p>Neural networks were developed using observations of wintertime peak wind speed, wind direction, and directional deviation collected from March 1995 through March 1999. Using current and past values of the observed elements, the networks produced 16 forecasts of peak wind speed. The first forecast was valid for 30 minutes past forecast start time, the second for 1 hour past start time, etc., up to 8 hours past start time, for any start time.</p> <p>Network performance was compared to three other forecasting options: persistence, climatology, and randomly selecting wind speeds from a climatologically based distribution. For forecasts at the end of the forecast period, networks that were tested with data near in time to the networks' training data showed skill over the other forecasting options.</p> <p>The results of this thesis provide a baseline for measuring future attempts at forecast improvements and establish the neural network approach as a potential means of enhancing peak wind speed prediction accuracy, especially for forecasts late in the forecast period.</p>				
14. SUBJECT TERMS Neural Nets, Meteorology, Weather Forecasting, Wind			15. NUMBER OF PAGES 131	
			16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT UNCLASSIFIED	18. SECURITY CLASSIFICATION OF THIS PAGE UNCLASSIFIED	19. SECURITY CLASSIFICATION OF ABSTRACT UNCLASSIFIED	20. LIMITATION OF ABSTRACT UL	

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. Z39-18
298-102